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Strategic Identification and Evaluation Using Machine Learning and Fuzzy Logic in Teacher Training

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Classroom teachers influence the learning environment, are responsible for designing appropriate teaching modes and making appropriate changes in order to meet current education standards. The training of teaching staff requires complex assessments of the teacher's skills and the ability of the student, as well as the quality of teaching and the current educational standards. Therefore, in this paper, the researcher propose a Development-focused Training Strategy by assimilating conventional machine learning and fuzzy logic for maximum-fit outcomes. First, the training process is based on the current educational standards and staff skills. The ability of the staff to learn and adapt to the new standards is analyzed using a recurrent neural network (RNN). This learning network trains its computing layer based on the previous adaptability level and the range of current standards. The minor difference between the standards is overcome by recommending additional training sessions for the teaching staff. Fuzzy logic is applied to identify the maximum amount of improvement achieved through the training. The complex processing part is filtered using the maximum fuzzy derivative on the achievement obtained from the previous session. Based on the results achieved, the computing layer's adaptability is flexibly adjusted. This improves to determine a more effective strategy without interrupting any training session.

Keywords: Fuzzy Logic; Machine Learning; Pedagogical Staff; Staff Training

1. INTRODUCTION

Pedagogical training involves training teachers to create a classroom environment that is conducive to student learning. Pedagogical training improves teachers' skills and teaching quality, thereby maximizing the academic growth of students [1]. Professional development sessions can help teachers to improve and refine their teaching skills. The aim of providing additional training to the teaching staff is to develop their knowledge, communication skills, and ethical knowledge [2]. A technological pedagogical content knowledge (TPACK) method is used in staff training systems. TPACK is mainly used to train pre-service teachers [3]. A qualitative analysis technique is used in TPACK which collects the necessary information for the training process. The qualitative analysis technique reduces the complexity of the strategic planning process, thereby improving the feasibility and effectiveness of staff training systems [4, 5]. Pedagogical training is also used to improve the pedagogical knowledge (PK) and content knowledge (CK) of learners. The pedagogical training helps teachers to understand the content of the session and to learn about best-teaching practices [6].

Strategic evaluation methods are used to evaluate the stability and feasibility range of the pedagogical staff training process. The main aim of the evaluation method is to provide optimal information for the training development process [7].

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An educational process and data mining (EPDM) model is used for the strategic evaluation process. A feature extraction method is used in the model to extract the emotional and sentiment features of teachers [7]. The extracted features produce the data necessary for the evaluation process. The EPDM model evaluates the specific types of strategies based on the features [8]. A statistical analysis technique is also used for the strategic evaluation process. The statistical analysis technique identifies the content which is relevant to staff training strategies [9], and also detects the actual emotional range of teachers which minimizes the latency in the further evaluation process. Technology-enhanced learning (TEL) method is used to analyze the learning abilities of teachers [10]. The TEL method comprises high-quality education details from colleges and institutions of higher learning, which reduces the time required to classify the data. The TEL method evaluates the exact abilities of teachers that, in turn, ensure the academic growth of the learners [11].

Machine Learning (ML) techniques are used in educational institutions to evaluate the pedagogical training process. The ML technique is mostly used to improve the accuracy of the evaluation results [12]. A reinforcement learning (RL) approach is used to evaluate the pedagogical training. The RL approach determines the effective empirical features which are used in the training process [13, 14]. The RL approach improves the effectiveness of pedagogical training systems. An ML-based educational data mining (EDM) model is also used to evaluate the training abilities of learners. The focus is on evaluating the pedagogical abilities of teachers as they participate in the training programs and improve their teaching skills [15]. ML is used in EDM to determine the teaching ability, communication skills, and interpersonal skills of teachers during the training period. The EDM model provides effective patterns for the evaluation process [16]. The EDM model increases the accuracy of evaluation which improves the effectiveness of training systems [17]. An evaluation method based on a genetic algorithm (GA) is also used to evaluate pedagogical training. The GA method evaluates the ethical features and teaching features of teachers, thereby reducing the latency in the professional development process. The GA-based method increases the effectiveness pedagogical training systems [18, 19]. This article makes the following contributions:

- The design of a development-focused training strategy for evaluating the performance of pedagogical staff by means of strategic assessments.
- The combination of the functions of recurrent neural network and fuzzy logic for validating the skills and training improvements in terms of adaptability to current education standards.
- An analysis of performance data, and a separate comparative analysis to determine the efficiency of the proposed method for different sessions and skills.

2. RELATED WORKS

Okoye et al. [20] proposed an education process and data mining (EPDM) model-based approach for pedagogical teaching assessment. Both qualitative and quantitative analysis techniques are used in the model to extract the important emotions and sentiments of the students. Sentiment analysis is implemented in the model to analyze the actual emotional and behavioral aspects of students. The EPDM model provides valuable information that can be used to improve the students' performance.

Mohammadpour et al. [21] developed a performance-based method to determine teachers' content knowledge (CK) of mathematics and science. The proposed method is also used to identify the pedagogical knowledge (PK) level of teachers. The performance-based method trains teachers to develop positive personal traits which increase their ability to communicate effectively with students. This approach increases the quality of teaching which, in turn, enhances the academic development of students.

Cleovoulou et al. [22] introduced an equity pedagogy model for teacher education systems. The main aim of the model is to produce equity-minded teachers who can deliver effective teaching. The proposed model provides proper planning strategies for the teachers to learn a particular field or area during the learning period. An empirical analysis is used here to analyze the ability and knowledge level of teachers that enhance the overall effectiveness of teacher education systems.

Howell et al. [23] proposed a flipped classroom (FC) education mode for sustainable development (ESD). This method is intended to provide active learning opportunities and encourage students to engage in reflective practices. The FC is used here to create an efficient learning environment for the students. The reflective practices help students to acquire new knowledge. The proposed method enhances the sustainability and feasibility of students' learning process.

Jiang et al. [24] developed a new method for evaluating textbooks used for the teaching of business English. The exact pedagogical impact of textbooks is evaluated, providing optimal information to inform the teaching of the subject. The evaluation method also provides thinking skills and teaching skills for teachers which reduces the complexity of the further teaching process. The developed method increases the accuracy of evaluation which improves the critical thinking ability of the students.

Du et al. [25] introduced a Q methodology-based evaluation method for pedagogical development. The proposed method identifies the exact long-term effects of development programs. The method involves project-based learning (PBL) to identify the important variables influencing the learning process. Both internal and external phases are detected using the PBL technique which produces relevant data for the development process. The proposed evaluation method improves the feasibility of pedagogical training.

Tondeur et al. [26] proposed a technological pedagogical content knowledge (TPACK) method for pre-service teachers. A synthesis of qualitative evidence (SQD) model is implemented in the model to determine the relationship between teachers and students. The TPACK method provides teachers with effective teaching skills and pedagogical knowledge. Experimental results show that the proposed TPACK method enhances the potential range of teachers.

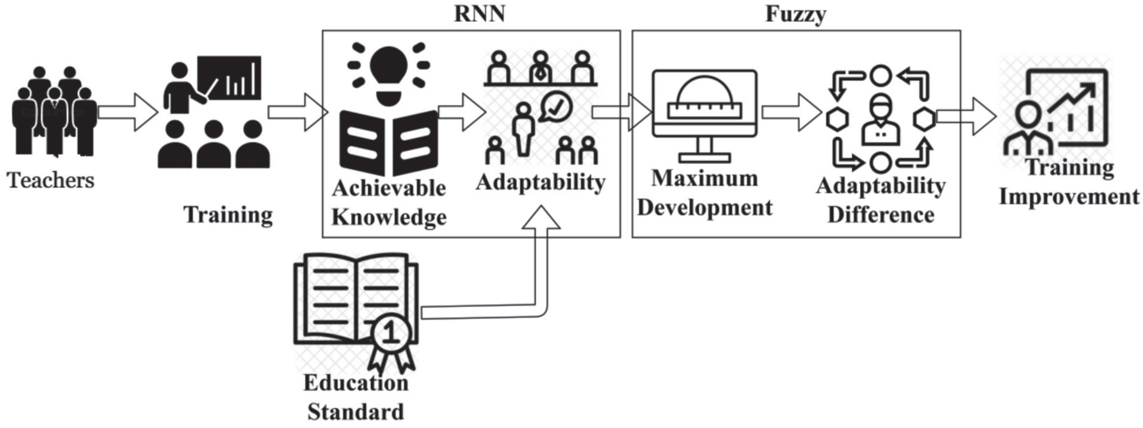


Figure 1 Functional representation of the proposed method.

Gideon et al. [27] designed a new method to address pedagogical and epistemic uncertainty in teacher training programs. The main aim of the method is to evaluate the strategies used to train the teachers. The proposed method uses feedback in order to learn the key characteristics of the teachers. The method improves the performance and effectiveness of teachers during the learning period.

Deng et al. [28] proposed a technological pedagogical content ethical knowledge (TPCEK) to develop and validate an assessment instrument for pre-service teachers. The proposed model is used as an assessment instrument that identifies the abilities of pre-service students. The model involves questionnaires as part of an exploratory analysis of the quality of the teachers. The proposed TPCEK model develops teachers' ethical knowledge and pedagogical knowledge.

Schultz et al. [29] introduced a pedagogical approach for primary palliative care (PPC), the main goal of which is to provide high-quality clinical care skills for the learners. A qualitative analysis technique is used in the approach that analyzes the optimal information obtained for the teaching process. The qualitative approach reduces the time and effort required for the learning. The proposed approach improves the academic performance of PPC students.

Myllykoski-Laine et al. [30] developed a supportive pedagogical culture framework for teaching and pedagogical development. Optimal practices and structures are provided to teachers which increases their learning abilities. Pedagogical cultures are identified using feedback that hastens the learning. When compared with other frameworks, the proposed framework enhances the effectiveness of teaching training programs.

Ma et al. [31] proposed a self-supervised pre-training (SPAKT) knowledge-tracing method. Theya deep learning (DL) model to train the self-supervised skills of teachers. The DL model identifies the skills set which is necessary for effective teaching. The DL model provides optimal performance and knowledge to train the teachers. The proposed SPAKT method increases the performance of knowledge-tracing systems.

Classroom teachers play a vital role in shaping the learning environment, designing effective teaching modes, and ensuring adherence to educational standards. However, training these staff members necessitates comprehensive assessments in order to take student and teacher skills into account, as well as educational standards and quality.

3. DEVELOPMENT-FOCUSED TRAINING STRATEGY USING CONVENTIONAL MACHINE LEARNING AND FUZZY LOGIC

The Development-Focused Training Strategy proposed in this study combines conventional machine learning with fuzzy logic to improve teacher training. By leveraging a recurrent neural network and fuzzy logic system, this strategy optimizes staff adaptability to new educational standards and identifies effective training methods. This iterative process ensures that the strategy remains agile and responsive to the evolving requirements of both the staff and the educational standards. By fine-tuning the adaptability of the computing layer, the strategy improves its ability to identify the most effective training methods. The function of the proposed method is illustrated in Figure 1.

This approach not only maximizes the development of teachers but also contributes to the overall improvement of the education system. This fusion of techniques facilitates continuous improvement and ensures maximum-fit outcomes in education without disrupting ongoing training sessions. Teachers play a crucial role in ensuring that educational standards are met. They are responsible for assessing and evaluating the quality of teaching, curriculum, and student progress. Through observation, feedback, and continuous professional development, they strive to maintain and improve educational standards, ensuring that students receive a high-quality learning experience. Teachers are trained to extract the achievable knowledge and then the adaptability by using the RNN. They also help to determine the effectiveness of the existing education system. The provision of training to teaching staff is expressed by Equation (1):

$$\left.\begin{array}{c} Z_j = w_j\left(\sum_j w_j.Z_j\right) \\ Z\left(w_j\right) = \frac{1}{1+e^{-Z_j}} \\ Z_j = \sum_j w_j.Z_j \\ \sum_{ij}(Z) = \frac{e^{ZW}}{\sum_{i=1} e^{Z_j}} \\ \partial Z = \frac{\partial Z\left(w_i, w_j\right)}{\partial Z_{ij}}(ZW) \\ \partial j = j\left(Z_j\right)\sum_{i=1}\partial Z.w_{ij} \\ \frac{\partial Z}{\partial w_{ij}} = \partial j z_j \end{array}\right\} \quad (1)$$

Where Z is the training given to the teachers, j is the checking process of the existing education system, W represents the standards of current education, and i is the curriculum evaluation. This training process helps to improve teacher skills and efficacy. Efficient training programs are provided to teacher to improve their skills and expertise. These programs focus on areas such as instructional strategies and the integration of technology in education. Through this training, teachers acquire valuable knowledge and practical tools to improve their teaching methods, promote student engagement, and stay updated with the latest educational practices. The skills improvement process is expressed by Equation (2):

$$\left.\begin{array}{c} GZ = \begin{cases} 1 & \text{if } G > n \\ e^{\left(1-\frac{n}{i}\right)} & \text{if } G \leq n \end{cases} \\ \sum_{n=i}(G) = GZ \cdot \left(\sum_{n=1}^{N} w_n \sum_{n=i} Z_n\right) \\ Z_G = \frac{Z \cdot W}{Z \cdot W + (1-G) \cdot G} \\ G^{(n)} = \phi\left(W^{(n)} + W^{(n-1)} + Zg\right) \\ i^{(n)} = \phi\left(W^{(n)} + W^{(n-1)} + Zi\right) \\ j^{(n)} = \phi\left(W^{(n)} + W^{(n-1)} + Zj\right) \\ W^{(n)} = \phi\left(W^{(i)} + W^{(i-1)} + Zn\right) \end{array}\right\} \quad (2)$$

Where G represents the improved skills of teachers. Now after the training session, the achievable knowledge and adaptability of the staff are facilitated by the RNN. The use of RNNs enables the verification of acquired knowledge, which is valuable for teachers. After training, RNNs help assess the students' understanding and retention of information. This verification process involves analyzing the patterns and sequences in student responses, identifying areas of strength and weakness, and providing insights to educators. After the training session, the RNN helps to determine the knowledge acquired as a result of the training session. The process of verifying the outcome of the training of teachers is expressed by Equation (3):

$$\left.\begin{array}{c} i_n = \eta\left(w_i\left[Z_{t-1}, w_t\right] + Z_i\right) \\ \tilde{i}_n = \sum_{n=1}\left(w_i\left[Z_{t-1}, w_t\right] + Z_i\right) \\ i_t = Z_t \odot i_{t-1} + it \odot \tilde{Z}_t \\ Z_t = \eta(w_0\left[\left[Z_{t-1}, i_t\right] + Z_0\right] \\ Z_t = w_t \odot \sum_{n=1}(Zt) \\ w_{ij} = \eta\left[w_i\left[Z_{t-1}, Z_t, Z_{t+1}\right] + w_j\right] \\ j_t = \eta\left[w_i\left[Z_{t-1}, Z_t, Z_{t+1}\right] + w_i\right] \end{array}\right\} \quad (3)$$

Where η represents the outcome of the training session. After a training session, evaluating the acquired knowledge becomes crucial for teachers. The RNN is used to evaluate the knowledge acquired by the teachers as a result of their training. This evaluation process assesses how well teachers have understood and retrained the material presented during their training, rather than a lesson delivered to students. The focus is on the teachers professional development and their ability to apply what they have learned in their teaching practives. It involves assessing the extent to which students have comprehended and retained the taught material. These assessments allow educators to gauge individual and overall understanding, identify areas that need reinforcement, and make informed decisions on instructional strategies. Additionally, qualitative feedback and classroom observations contribute to a comprehensive evaluation. By analyzing the achieved knowledge, teachers can adjust their teaching approaches, address knowledge gaps, and provide targeted support to improve the learning outcomes of their students. Effective evaluation empowers educators to continuously improve their teaching practices and promote student success. The process of determining the achievable knowledge after the training session is explained by Equation (4):

$$\left.\begin{array}{c} Z^{(n)}: Q^{n-1} \rightarrow Q^n \\ Z \longrightarrow Z^{(n)}(Z) \\ \left(\phi\left\langle w_1^{(n)}, Z\right\rangle, \ldots, \phi\left\langle wQ_n, Z\right\rangle\right)^T = \phi\left\langle w^{(n)}, Z\right\rangle \\ Z^{(i:1)} \quad Q^0 \rightarrow Q^1 \\ g \in Q^0 \rightarrow \phi\left\langle w_1^{(i+1)}, Z^{(i:1)}(g)\right\rangle \\ i = (i_1, \ldots, i_T) \\ t = 1, \ldots, T \\ i_T \in Q^0 \end{array}\right\} \quad (4)$$

Where ϕ is the achievable knowledge of the teachers after the training session, and Q denotes the learning establishments refers to the educational institutions or environments where the students can learn. The learning establishments encompasses the overall framework, including schools, colleges, or any educational settings where teaching and learning occur. Now the adaptability to the current education system is determined by using the RNN based on the education standard. Education standards serve as benchmarks to evaluate the adaptability of teachers. These standards outline the knowledge, skills, and competencies expected of educators to meet the evolving needs of students. The RNN process for computingϕ is illustrated in Figure 2.

In Figure 2 the possibilities for $G \times W \ \forall \ i$ across Q or η extraction is pursued. Based on W the matching of $G \ \forall j$ is undertaken. In this process, the $Q \ \forall \ i$ and $\eta \ \forall \ W$ (matching) are validated separately. In this case the $Z^n \ \forall \ Q^{n-1}$ (Previous) and Q^n (current) are induced for handling skill improvements. Thus, either the first/ previous instances are required for leveraging the η by satisfying $i_T \in Q^o$. Therefore, adaptability is considered as a means of providing consecutive development through training. Thus, the recurrency is induced for Q alone in the verification of skill-based adaptability. By aligning instructional practices with these standards, teachers demonstrate their ability to adapt to changing educational landscapes. Evaluation criteria may include classroom management, instructional strategies, student engagement, differentiation, assessment techniques, and professional development participation. Adaptable educators stay abreast of current research, embrace innovative teaching methods, foster inclusive learning environments, and continuously reflect and refine their practices to meet the diverse needs of their students. The process of extracting the present education standard for the further adaptability verification of the teachers is expressed by Equations (5) & (6):

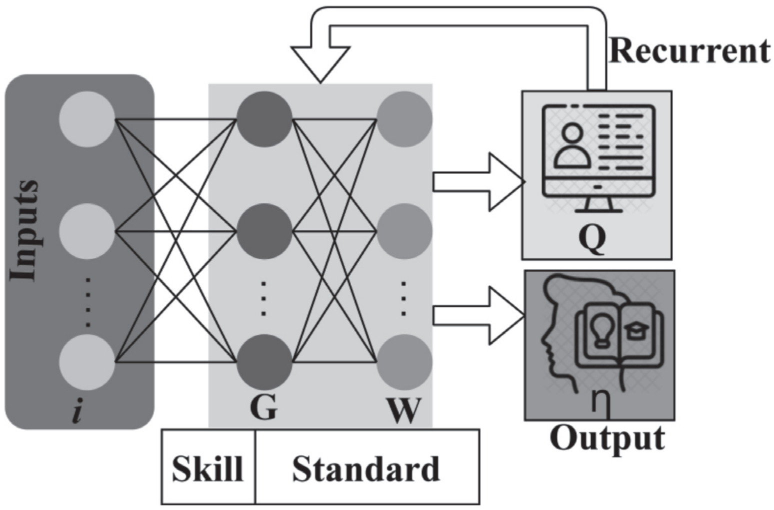


Figure 2 RNN process for computing ϕ.

$$\left.\begin{array}{c} M_t^{(1)} = M^{(1)}\left(Zt, M_{t-1}^{(1)}\right) \\ M_t^{(2)} = M^{(2)}\left(Zt^{(1)}, M_{t-1}^{(2)}\right) \\ M_t^{(1)} = M^{(1)}\left(Zt, M_{t-1}^{(1)}, M_{t-1}^{(2)}\right) \\ M_t^{(2)} = M^{(2)}\left(Zt^{(1)}, M_{t+1}^{(2)}\right) \\ \phi\eta\,(Z) = \frac{1}{1+e^{-Z}} \in (0,1) \\ \phi \sum_{n=1}(Z) = \frac{e^{Z}-e^{-Z}}{1+e^{-Z}} = 2\phi(2Z) \\ Gt^{(1)} = G^{(1)} \cdot (Zt, G_{t-1}) \\ = \phi\eta\,(\langle w_t, Z_t\rangle) \in (0,1) \end{array}\right\} \quad (5)$$

$$\left.\begin{array}{c} K = W_x.Zt + K_j \\ K = \frac{1}{N}\sum_{i=1}(t_i - K_j)^2 \\ w_{Ki} = \sum_{n=1}\frac{\partial K}{\partial W_K} \\ I_{(i+1)}^t = \overrightarrow{K}_i^t \oplus \overleftarrow{K}_{ij}^t \oplus \overrightarrow{K}_i^t \oplus \overleftarrow{K}_{iZ}^t \\ K^t = \overrightarrow{w}.\overrightarrow{k}^t + \overleftarrow{w}\,\overleftarrow{k}^t \\ K = \sum_{t=0} Z^t \\ G(K_i) = \frac{e^K}{\sum_{i=0} e^{K}i} \end{array}\right\} \quad (6)$$

Where M denotes the education standard, K represents the teaching methods used in the current education system. Now based on this education standard, the adaptability of the teachers occurs by using the RNN. RNNs are utilized to evaluate the adaptability of teachers following a training session. By analyzing patterns in instructional strategies, student engagement, and classroom management, RNNs provide insights into the adaptability of educators. This evaluation helps to identify the areas where staff successfully adapt their teaching approaches and areas that require improvement. RNNs offer a data-driven approach to assess and enhance the adaptability of teachers, leading to more effective teaching practices and improved student outcomes. The process of evaluating the adaptability using the RNN is explained by Equation (7):

$$\left.\begin{array}{c} P(t) = G(Z(W(t))) \\ P(t) = G(W(t)) \\ G(t) = (Z(W(t-1), Z(t)) \\ P_j(t) = W(t) \\ \sum_{n=1}(t) = \sum_i P_i(t) w_{ij} + \phi_j \\ P_j(t) = \sum_{n=1}(t_{ij}) \\ P_K(t) = G(t_{ij}) \\ \sum_{n=1}(P_K) = G_j + \eta_j \end{array}\right\} \quad (7)$$

Where P is the adaptability of the teachers after the training session. The efficiency of adaptability in the current education system is a critical consideration, as it is continually evolving to meet the changing needs of students and the demands of the modern world. An adaptable approach allows educators to respond effectively to diverse learning styles, emerging technologies, and evolving pedagogical practices. It promotes personalized learning, inclusivity, and the cultivation of essential skills. Efficient adaptability ensures that the education system remains relevant, prepares students for the future, and fosters a dynamic and engaging learning environment. Assessing the effectiveness of adaptability helps to ensure that education meets the evolving needs of students and society. The verification of adaptability, whether or not it is based on the current education system, is expressed by Equation (8):

$$\left.\begin{array}{c} Z(P) = \sum_{i=1} G_{ij}(Z_i) + \sum_{i<j}\phi_P(i,j) \\ Z_1(t) = \begin{cases} \sum_{n=1}(M) & t = 0 \\ \sum_{n=1}(t-1) & 0 < t \le T \end{cases} \\ Z_2(t) = \sum_{n=1}(G, p, J), \quad 0 \le t \le T \\ \phi(t) = \begin{cases} 0 & 0 \le t \le T \\ Z_2(t) & t = T \end{cases} \\ Z(\phi) = \begin{cases} \sum_{n=1}(G) & t = 0 \\ \sum_{n=1}(Z(\phi)) & 0 < t \le T \end{cases} \end{array}\right\} \quad (8)$$

Now the output of the RNN process is given as the input to the fuzzy logic process to extract the maximum development

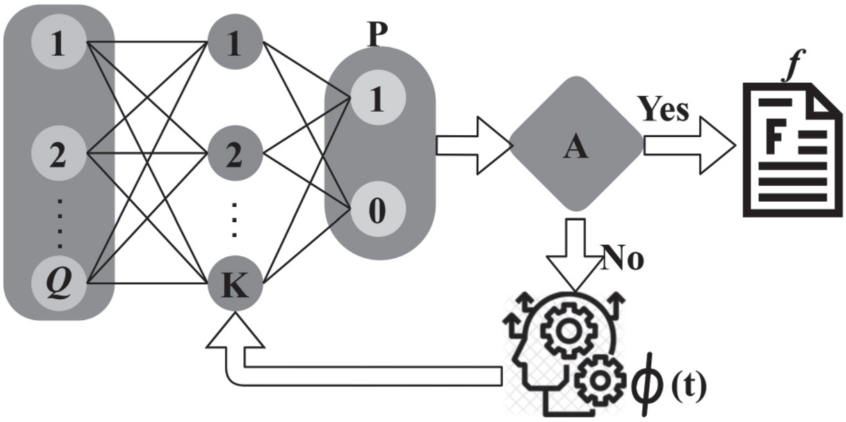


Figure 3 Output using RNN process.

and then the difference in adaptability after the training session. The evaluation of maximum development by fuzzy logic after a teacher training session indicates the extent to which their skills and competencies have improved. Fuzzy logic helps to analyze the staff's performance, identify areas of growth, and measure the effectiveness of the training. By using fuzzy logic, more comprehensive and nuanced assessments are made, enabling a better understanding of the teachers development, and determining whether further training is required. The evaluation of the maximum development of teachers by means of fuzzy logic is expressed by Equation (9):

$$\left.\begin{aligned} A &= \left\{\tfrac{(Z,\phi A(Z))}{Z} \in G\right\} \\ f(Z{:}\phi, P) &= e^{-Z}/2Z^2 \\ \textstyle\sum_{n=1}\left(A_{ij}\right) &= \frac{\int_0^1 f(Z)ZdZ}{\int_0^1 f(Z)dZ} \\ \textstyle\sum_{n=1}\left(G_i(A_j)\right) &= \frac{\sum_{n=1}(A_{ij})}{\sum_{n=1}(G_{ij})} \end{aligned}\right\} \tag{9}$$

Where A represents the maximum development, and f denotes the output of the RNN process. The output using the RNN process is illustrated in Figure 3.

Figure 3 above presents the RNN output extraction from Q. As η is filtered from the entire output, then K is validated for the available Q such that P is either 0 or 1. If the P is 1, then A is achievable and therefore f is concluded. Conversely, if it is not achievable as indicated by $P = 1$ or 0 then $\phi(t)$ is required as a part of $Z(P)$ to improve recurrent analysis (Figure 3). The development of skills and career knowledge by fuzzy logic after a training session involves assessing the growth and advancement of teachers in their professional journey. Fuzzy logic provides a flexible and comprehensive approach to evaluating their skills, expertise, and understanding of their field. By considering various parameters and degrees of achievement, fuzzy logic enables a nuanced analysis of teachers' career development, helping to identify strengths, weaknesses, and potential areas for improvement to guide their ongoing professional growth. Equation (10) below is used to estimate the improvement in skills and career knowledge after the training session.

$$\left.\begin{aligned} \mu(Z_i) &= \begin{cases} \frac{Z_i - W_1}{W_2 - W_1} & W_1 \le Z_i \le W_2 \\ \frac{W_3 - Z_i}{W_3 - W_2} & W_2 \le Z_i \le W_3 \\ 0 & \text{otherwise} \end{cases} \\ \mu(Z_i) &= \begin{cases} \frac{Z_i - W_1}{W_2 - W_1} & W_1 \le Z_i \le W_2 \\ 1 & W_2 \le Z_i \le W_3 \\ \frac{W_4 - Z_i}{W_4 - W_3} & 3 \le Z_i \le W_4 \\ 0 & \text{otherwise} \end{cases} \end{aligned}\right\} \tag{10}$$

Where μ denotes the estimated improvement of skills and career knowledge after the training session. Now by using the fuzzy logic process, the adaptability difference is identified after determining the maximum development after the training session. The evaluation of adaptability differences using fuzzy logic after a training session involves assessing how effectively teachers members have adapted to new methodologies, technologies, or changes in the educational landscape. Fuzzy logic enables a nuanced analysis by considering various factors and degrees of adaptability. It helps measure the extent to which staff members have embraced and implemented new approaches, overcome challenges, and demonstrated flexibility in their teaching practices. By utilizing fuzzy logic, a comprehensive evaluation can be conducted, providing insights into individual adaptability differences and guiding further support or training initiatives if necessary. The evaluation of the adaptability difference by means of fuzzy logic is expressed by Equation (11):

$$\left.\begin{aligned} F &= \frac{\sum_{i=1}^{n} Z_i G_i}{\sum_{i=1}^{n} Z_i} \\ F &= \frac{\sum_{i=1}^{n} G_i(w)}{\sum_{i=1}^{n}(w)} \\ F &= \frac{\sum_{i=1}^{n} W_i(Z_i)}{\sum_{i=1}^{n} W_i} \\ T &= \frac{\sum_{i=1}^{n} f W_i(W_i G_i)}{\sum_{i=1}^{n} W_i} \end{aligned}\right\} \tag{11}$$

Based on the previous behavior, the extent to which there is a difference in adaptability is estimated. In the operation used to estimate differences in adaptability, the previous behavior of individuals is considered. By analyzing their past responses to changes, challenges, and new methodologies, the operation assesses the degree of adaptability exhibited by each individual. This estimation provides insights into their

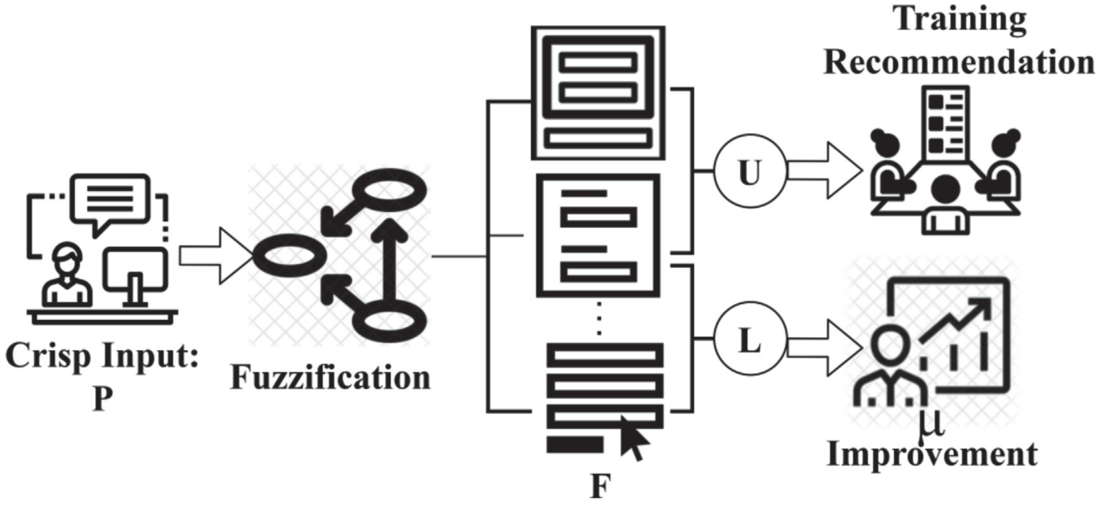


Figure 4 Estimation of adaptability differences using fuzzy logic.

ability to adjust, embrace innovation, and effectively navigate evolving educational contexts. Then the adaptability-based recommendation is provided if there are any issues in the training session. The process of determining the previous behavior for the adaptability difference is expressed by Equation (12):

$$\left.\begin{array}{c} \frac{Udw}{dt} = -U + T - T_{ij} \\ \frac{dw}{dt} = U \\ w_e = w_{ij} - w \\ w_{ij} = w_e - w_{Zj} \\ w_e = w_{ij} - U_{ij} \\ U_i = T_{ij} + T_i \sum_{j=0} w_{ij} \end{array}\right\} \quad (12)$$

Where U represents the difference in adaptability. Now the training improvements are determined after the RNN and fuzzy logic processes after the teacher-training session. Improvements in teacher training are achieved by incorporating adaptability-based recommendations. After assessing the adaptability levels of staff members, training programs are customized to address specific areas for improvement. These recommendations may include strengthening problem-solving skills, promoting flexibility and resilience, and fostering a growth mindset. The fuzzy logic process used to estimate differences in adaptability is presented in Figure 4.

The crisp input range of P is validated for different F across U and L. In this differentiation process, F and T are categorized so as to improve fuzzification. The differentiation achieves U or L by which development progress is identified. Hence, in this case, the training recommendation or μ improvement or both is provided. Thus, fuzzification is utilized to maximize strategy precision (Figure 4). Through targeted training sessions, staff members acquire strategies enabling them to navigate changes in education effectively, embrace innovative methodologies, and adapt to the evolving needs of students. This approach ensures that training interventions align with individual needs, promoting continuous professional growth and enhancing the overall effectiveness of teachers. The process of training improvements is expressed by Equations (13) & (14):

$$\left.\begin{array}{c} L \leftrightsquigarrow \mu_A(Z) = \begin{cases} 1 & \text{if } Z \in A \\ 0 & \text{if } Z \notin A \end{cases} \\ F = \{(Z, \mu(Z))\} / Z \in G\} \\ (Z, \mu_F(Z)) \qquad \forall Z \in G \\ F = \int \frac{LF(Z)}{Z} \\ Z = (Z_1, \ldots, Z_G)^T \\ L \leftrightarrow \mu_F(Z) = \begin{cases} 1 & \text{if } Z \in F \\ 0 & \text{if } Z \notin F \end{cases} \end{array}\right\} \quad (13)$$

$$\left.\begin{array}{c} C(Z) = \frac{W_1 + W_2}{2} \\ Z^{(t)}, w^{(t)} \\ t = 1, 2, \ldots, N \\ \overline{A}_T = w_{i=1} A^1 \\ W^{(t)} = \prod_{\eta=1} \mu_A(Z(t)) \\ w = 1, 2, \ldots, n \\ C = 1, 2, \ldots, n \end{array}\right\} \quad (14)$$

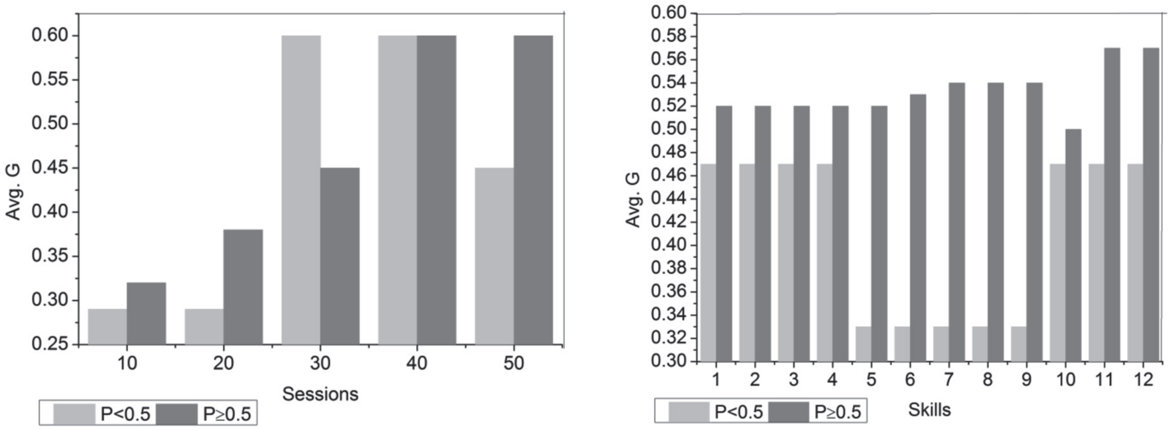
Where L represents the training improvements, C denotes the adaptability-based recommendations. This method helps to improve the training by incorporating the functionalities of RNN and fuzzy logic. These technologies work together to enhance the adaptability of the training process, allowing for more precise identification of the training process, allowing for more precise identification of effective strategies without interrupting ongoing training sessions. The adaptability of the computing layer is flexibly adjusted based on the achieved development. This adjustment enables a better identification of strategy precision without interrupting any ongoing training session. By dynamically adapting the computing layer, data can be efficiently processed and analyzed, making real-time adjustments to optimize strategy precision. This enables the seamless integration of adaptive algorithms and models, enhancing the training session's effectiveness without causing any interruptions or disruptions to the learning process.

4. DATA COLLECTION AND ANALYSIS

Information collected from 70 individuals provided data for [32]. The individuals working in Finnish universities are identified under a fundamental pedagogy course evaluated

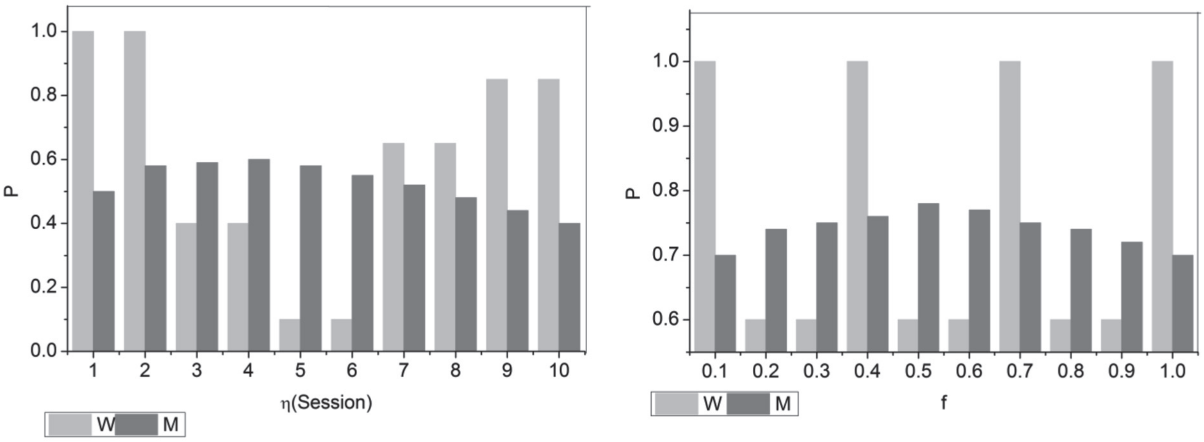
Table 1 Study course design.

Fundamental Levels	Training Sessions	Result
Video-Learning	5 Weeks	G, L
Questionnaire	2 Weeks	U
Theories	7 Weeks	Z, U
Knowledge Transmission	2 Weeks	L
Misconceptions	3 Weeks	Z



(a) (b)

Figure 5 Avg. G analysis.



(a) (b)

Figure 6 P analysis.

using a dedicated credit transfer and accumulation system. The study course design is shown in Table 1.

As presented in the table above, the training sessions for different fundamental levels are analyzed. The scoring system is based on the skills and development observed at the end of various training sessions. Taking into account the available statistical data, the skill and performance-based (score) analysis is presented. First, the average G for 70 staff for all sessions and skills is shown in Figure 5.

The above analysis of data for the 70 staff is based on their scores. For the sessions, the improvements range between 0.29 and 0.6 with fluctuations for $P < 0.5$. For $P \geq 0.5$, the avg. G increases steadily. The retained/halted sessions are validated based on the previous (U, L) whereas this case is different for skill-based analysis. The steep improvement is handled using $P \geq 0.5$ for a maximum of 0.57 of avg. G. Therefore, compared to the sessions the skills are prominent in deciding the μ. This shows the adaptability of the staff to the updated/ new educational standards. Thus, standard-based adaptability verification becomes the next main assessment step. The adaptability assessment for η and f are analyzed, as shown in Figure 6.

The P variations for (W, M) over the varying η and f in analyzed in Figure 6. The RNN process is void of two outputs

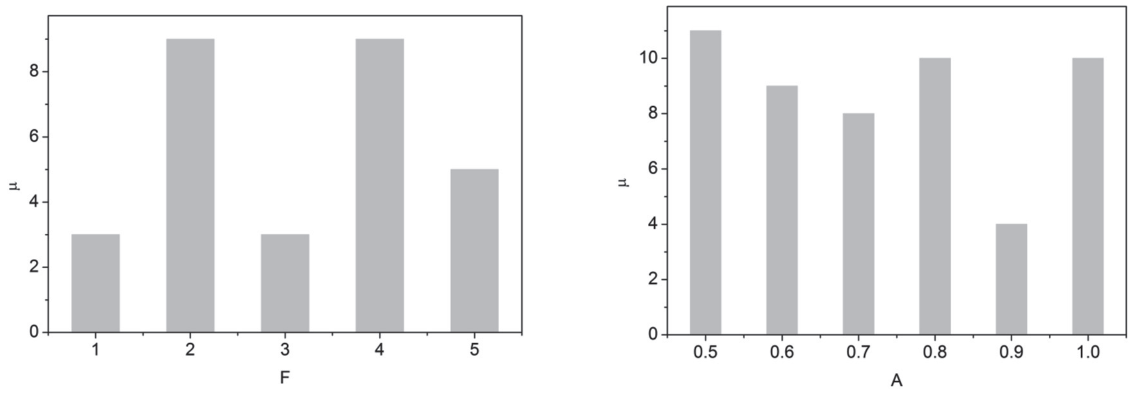


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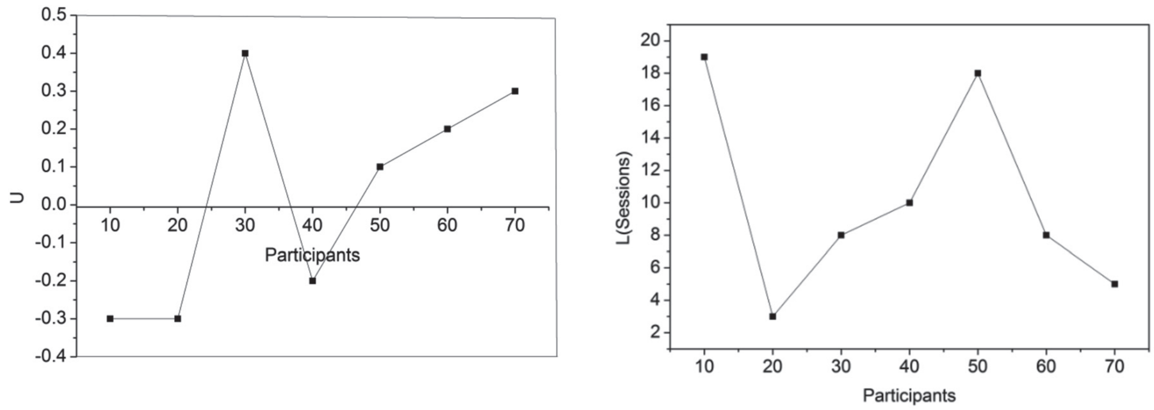
Figure 7 μ analysis based on F and A.



(a) (b)

Figure 8 U and L analysis.

(i.e.) Q and A at regular intervals (post-session completion). Therefore, the optimal sessions that are to be augmented are accounted for in η (1 to 10). For the accounted process P improvements are high for W compared to M. In the case of f, the $Z(P)$ determines the A for which W experiences more variations than M. At the end of the recurrent process, based on A availability the $\phi(t)$ determine the P due to which $W > M$. Pursued by the P the μ for different F and A is analyzed, as shown in Figure 7.

The μ output relies on RNN and fuzzy outputs for improving personal and pedagogical skills. The skills associated with different P improvements are valid for differentiating F. The differentiated F is used for L and C provided the M is satisfied. This satisfaction is perceived for ϕ and, therefore, steep improvement is achieved. Therefore, the available A rate is incremented for new derivatives for increasing μ. Thus, the consecutive process is required for differentiating F and A across various μ satisfying M (Refer to Figure 7). Finally, the U and L combination for a cumulative peek of 70 persons is given in Figure 8.

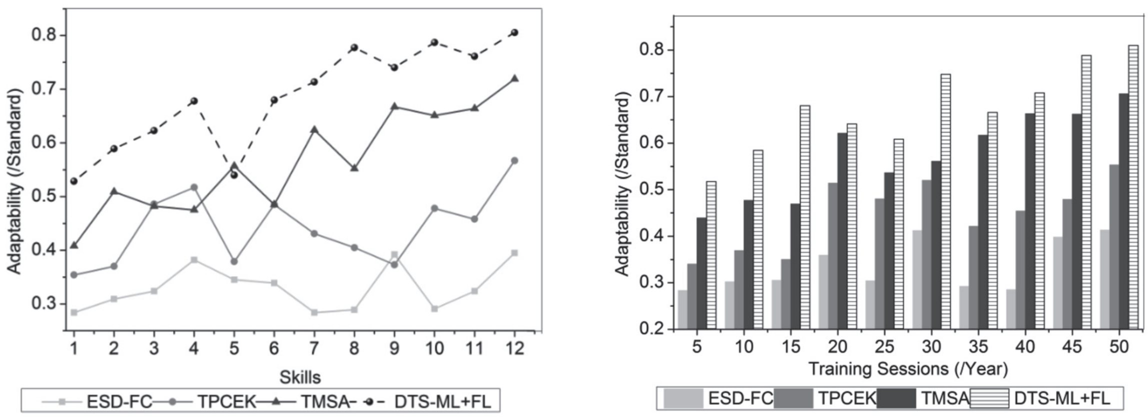
In Figure 8, the U and L analysis is used to validate different participants. The proposed method improves the selection and maximum fuzzy selection for providing C. If C is improved, then L improvement is necessary. Conversely, if the participants lack knowledge and various skills, then the U value exhibits unpredictable behavior in the system representing participants knowledge proficiency. Reducing abruptness in U is typically a goal for improving system ability and predictive accuracy. Thus, the recurrent processes on Q and P are periodically handled using multiple instances through the previous A. This reduces the consecutive L more so than the actual case.

5. DISCUSSION

This section discusses adaptability, strategy precision, interrupted sessions, training complexity, and precision computing time. The skills and the training sessions (/year) are varied in this assessment of performance. The methods ESD-FC [23], TPCEK [28], and TMSA [20] are handled along with the proposed method.

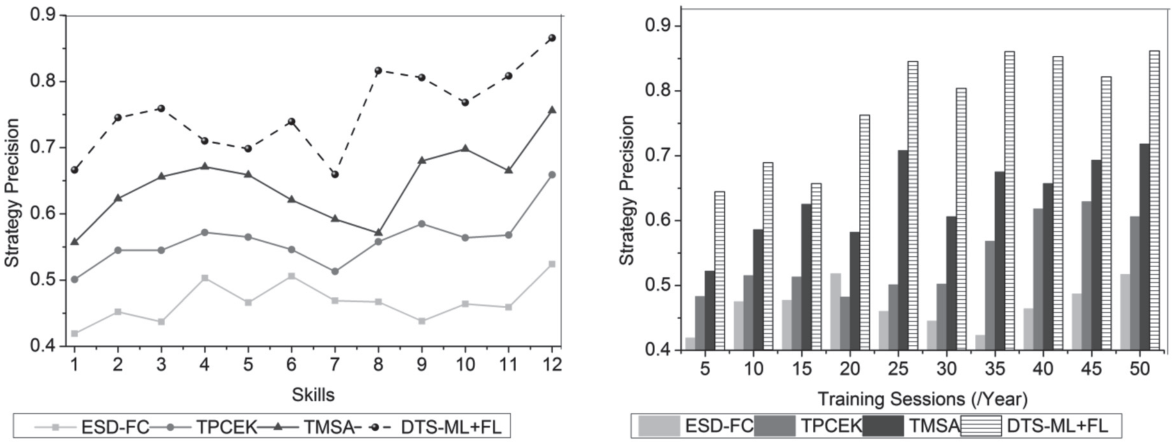
5.1 Adaptability

The adaptability is efficacious in this process by using the RNN with the help of the existing education standard. Efficacious adaptability, evaluated by Recurrent Neural



(a) (b)

Figure 9 Adaptability analysis.



(a) (b)

Figure 10 Strategy precision analysis.

Networks (RNN), plays a crucial role in teachers training. It refers to the ability of educators to effectively adapt their teaching strategies and approaches to meet the diverse needs of students. RNNs, a type of machine learning model, analyze patterns in student data and provide insights to educators, allowing them to tailor their instruction accordingly. By leveraging RNNs, teachers identifies optimal teaching methods, personalizes learning experiences, and promotes student engagement and achievement. This dynamic adaptability empowers educators to create a supportive and inclusive learning environment that maximizes student learning outcomes. Hence, the adaptability of the staff after the training session is enhanced with the help of neural networks (Figure 9).

5.2 Strategy Precision

The precision of the strategies is better in this process by using the fuzzy logic process and RNN. Better strategy precision is a crucial aspect of teachers training, aiming to enhance instructional effectiveness. It involves refining teaching strategies to achieve higher precision and efficacy in meeting desired learning outcomes. By employing evidence-based practices, data analysis, and continuous evaluation, teachers identifies and implements strategies that have proven to be more successful in promoting student learning. This may involve utilizing innovative teaching methods, incorporating technology, fostering active learning, and providing differentiated instruction tailored to individual student needs. By striving for better strategy precision, educators optimize their instructional practices, increase student engagement, and improve overall learning outcomes. It is an ongoing process that encourages educators to reflect, adapt, and refine their approaches to ensure that their teaching strategies are effective and aligned with the needs of their students (Figure 10).

5.3 Halted Sessions

There are fewer interrupted sessions as a result of using the outcome of the fuzzy logic and RNN operations. Reducing the number of terminated or interrupted teacher training sessions is a priority for optimizing the learning process. Fuzzy logic enables the modeling of imprecise or uncertain data, facilitating a more nuanced analysis of training sessions. By applying fuzzy logic to evaluate training effectiveness, an

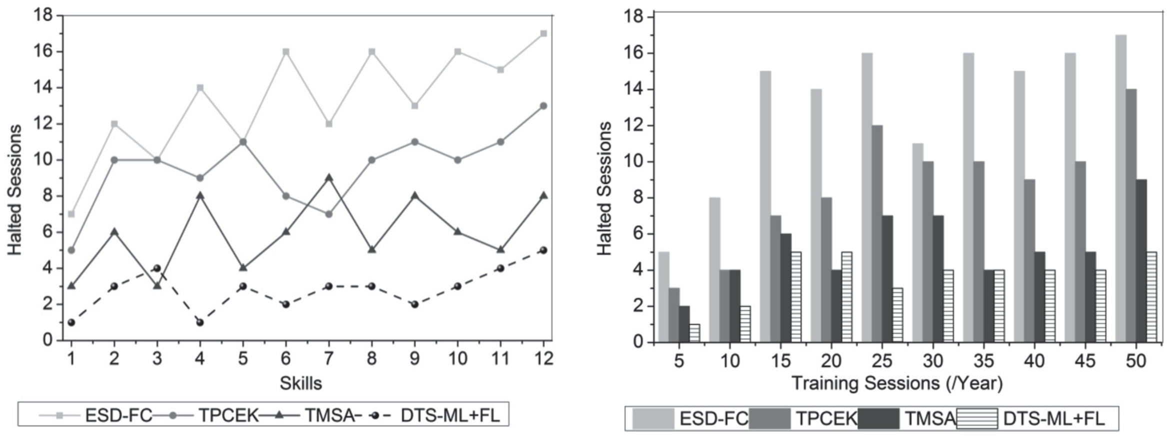


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Figure 11 Halted sessions analysis.

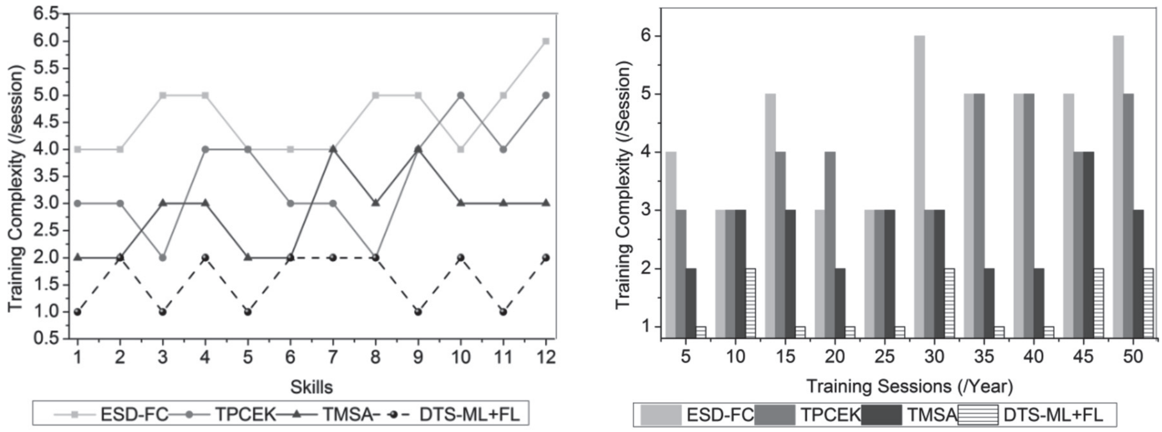

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Figure 12 Training complexity analysis.

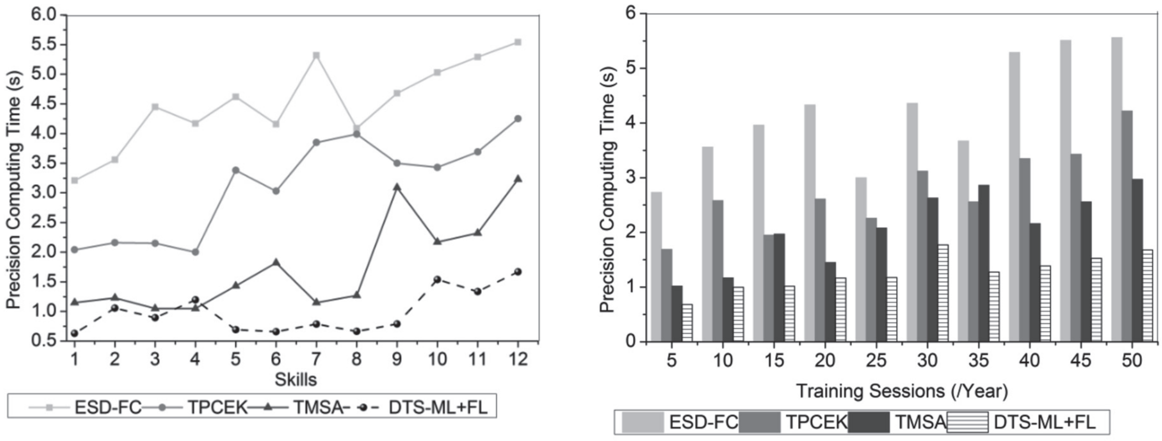
educator identifies potential areas requiring improvement, and develops targeted interventions. RNN, on the other hand, analyzes patterns in training data and provides insights into session effectiveness, helping to identify factors that contribute to halts and interruptions. By leveraging these technologies, teachers can proactively address issues, refine training strategies, and minimize disruptions, leading to more efficient and productive training sessions that enhance the professional development of educators. These strategies assist in reducing the number of interrupted sessions (Figure 11).

5.4 Training Complexity

The complexity of the training is less when the RNN operation is used to determine the achievable knowledge and adaptability. Reducing training complexity is a key objective of teacher training, and is facilitated by RNN. RNNs offer the potential to simplify and streamline the training process by analyzing complex patterns in student and instructional data. By leveraging RNNs, teachers gain valuable insights into the effectiveness of different training approaches, identify areas of improvement, and tailor their training strategies accordingly. The ability of RNNs to process sequential data makes them well-suited for capturing the intricate dynamics of the training process. By leveraging this technology, teachers optimizes their training programs, reduces unnecessary complexity, and focuses on strategies that yield the best outcomes. This results in more efficient and effective training experiences that enable educators to strengthen their skills and ultimately improve student learning (Figure 12).

5.5 Precision Time

The time taken for the precision is less in this approach as the efficacy of teacher training has improved. Decreasing precision time, or the time taken to achieve accurate and reliable results, is a significant objective in teacher training. Fuzzy logic contributes to achieving this goal by providing a more flexible and adaptive approach to data analysis. Fuzzy logic enables the representation and handling of imprecise or uncertain data, which is often encountered in



(a) (b)

Figure 13 Analysis of precision time.

Table 2 Results for skills.

Metrics	ESD-FC	TPCEK	TMSA	DTS-ML+FL
Adaptability (/Standard)	0.395	0.567	0.719	0.8055
Strategy Precision	0.524	0.659	0.756	0.8656
Halted Sessions	17	13	8	5
Training Complexity (/Session)	6	5	3	2
Precision Computing Time (s)	5.54	4.25	3.23	1.668

Table 3 Results for training sessions.

Metrics	ESD-FC	TPCEK	TMSA	DTS-ML+FL
Adaptability (/Standard)	0.413	0.553	0.706	0.8098
Strategy Precision	0.517	0.606	0.718	0.8617
Halted Sessions	17	14	9	5
Training Complexity (/Session)	6	5	3	2
Precision Computing Time (s)	5.56	4.22	2.97	1.678

educational contexts. By applying fuzzy logic techniques, teachers effectively analyze training data, identify patterns, and take less time to make informed decisions. This enables educators to quickly assess the effectiveness of training strategies, identify areas for improvement, and adjust their approaches accordingly. By leveraging fuzzy logic, teachers can streamline the training process, save time, and focus on implementing precise and targeted interventions that enhance professional development and ultimately benefit student learning outcomes (Figure 13). The results of the above discussion are presented in Tables 2 and 3 for various skills and training sessions, respectively.

The proposed method improves the adaptability and strategy precision by 12.26% and 10.96% respectively. This method reduces the number of interrupted sessions, the training complexity, and the precision computing time by 10.09%, 9.52%, and 10.26% respectively.

The proposed method improves the adaptability and strategy precision by 12.62% and 12.4% respectively. This method reduces the number of interrupted sessions, the training complexity, and precision computing time by 10.4%, 9.52%, and 10.09% respectively.

6. CONCLUSION

This article presents a Development-Focused Training Strategy that integrates conventional machine learning and fuzzy logic to achieve optimal outcomes. By utilizing a recurrent neural network and fuzzy logic, this strategy aims to improve training precision without interrupting ongoing sessions, thereby maximizing staff development. The training process commences by aligning content with current educational standards and evaluating the teaching staff's skills. To assess their ability to learn what is required to meet the new standards, a recurrent neural network is employed. This network's computing layer is trained based on the teachers' previous level of adaptability and the range of current standards. By considering these factors, the network identifies minor discrepancies between the previous and new standards, enabling the recommendation of additional training sessions for the staff members. After each training session, a fuzzy logic system evaluates each teacher's progress and calculates his/her achievement using the maximum fuzzy derivative. This approach effectively filters the complex processing components, focusing on the most significant aspects of development. By leveraging fuzzy logic, the strategy gains insights into the effectiveness of the training, and flexibly adjusts the adaptability of the computing layer. This refinement improves the precision of identifying effective training strategies while ensuring the uninterrupted continuation of training sessions. Based on the achieved results, the adaptability of the computing layer is dynamically adjusted. The proposed method improves adaptability by 12.26% and reduces the training complexity by 9.52% for different skills.

7. FUNDING

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