Improving Student Engagement in College Education with Fuzzy Control Algorithm

Yan Chen
Graduate Affairs Office, Chengdu University of Technology, China
ChenYan19970203@outlook.com

Abstract: *Student engagement in college education is a flexible, difficult notion involving participation in interactions, discussion, and performance outcomes in the classroom. It is crucial to anticipate the participation so that the teacher can comprehend whether the student engages with different tasks in the classroom by using fuzzy controllers. In the presence of non-linearities and model hesitations, linear Proportional-Integral-Derivative (PID) controllers may not execute acceptably; hence, fuzzy logic is employed. There isn't a single, reliable way to tell whether a student has been fully engaged in their college education. The current research aims to choose the most effective fuzzy control algorithm for improving students' engagement in the classroom. Hence, an Adaptive Mamdani Fuzzy Inference System (AMFIS) based PID controller using the Modified Salp Swarm (MSS) algorithm is proposed. Initially, the AMFIS is applied for expert system applications where the rules are generated from expert teacher knowledge based on student response indicators. The operational input is taken from the membership functions of indicator variables. In this study, a fuzzy PID-type controller is designed and presented to enhance student engagement by providing increased assessments and feedback through an expert decision process. Then, the MSS algorithm is utilized to optimize the scaling variables of membership functions, like improving the assessment counts and reducing the difficulty of curriculum to improve student engagement. The proposed algorithm's effectiveness is validated using metrics like Cronbach's alpha coefficient to find the control process's reliability, accuracy, engagement ratio, and error rate.*

Keywords: *Fuzzy controller, mamdani fuzzy inference system, adaptive control, modified salp swarm, engagement level.*

Received October 14, 2024; accepted April 26, 2025
https://doi.org/10.34028/iajit/22/4/2

1. Introduction

Improving educational outcomes and overall academic performance requires increasing student engagement in college education. The monitoring and analysis of numerous variables influencing student engagement, such as attendance enrollment, involvement, and academic success, could be done using a fuzzy control algorithm. A process or system can be regulated and controlled by fuzzy control algorithms, a form of control system. As mentioned earlier, the algorithm would use the variables as inputs, determining the involvement needed for each student.

Various fuzzy mathematical and statistical methods provide efficient teaching and learning to increase student involvement and their grasp of the teaching content; teachers must closely monitor students' involvement and performance in the classroom. By encouraging students to be more proactive and imaginative, the method of teaching and learning will be more successful and engaging. Class interaction should be two-way by involving the students in the discussion. Based on fuzzy set theory, fuzzy control is a computer model that uses fuzzy language and logic. Fuzzy control systems are digital automatic control systems based on fuzzy mathematics, fuzzy language form knowledge depiction, fuzzy logic rule inference, and a closed-loop architecture with a feedback channel using computer control technology. The adaptive supervisory control algorithm with optimization update has been used in numerous situations, including control systems. It has been demonstrated to be effective at optimizing challenging nonlinear functions due to the instability of student engagement levels. The fuzzy Proportional-Integral-Derivative (PID) controller is a discrete-time version of the traditional PID controllers that keeps the linear structure of the integral, proportional, and derivative components while introducing constant coefficients but self-tuned control gains.

Student engagement is crucial to teaching and learning since it is strongly connected to growth efficiency [28]. Student engagement measures a student's interpersonal contact and their level of participation and effort in activities that encourage endurance and achievement. Encouragement of student learning and development is said to depend on their level of engagement [5]. The difficult process is to get students to engage in problem-solving and research skills development in college education. Teachers use various outcome-based methods of instruction and learning that educationalists developed to motivate student participation [19]. Numerous education researchers have examined student participation from various angles, including student behaviours, a task performed by teachers, and institutional endeavours. A common example of an approach suggested in the research for promoting student involvement is flipped education [7].

Self-reporting was the main technique for assessing student involvement, making results more subjective than behavioural. There were variations in the context and paradigms of student engagement through computer technologies [25]. Fuzzy logic can improve students' engagement in online discussions, provide engagement between students and teachers, and increase subject-matter understanding only in online forums [23]. Hence, a two-tier fuzzy controller may recommend adjusting a student's grade following their social interactions and diagnosing the degree of engagement at the classroom level [18]. The approach fuzzy cognitive map is applied to detect the performance to handle a limited sample collection of student data in a classroom. Iatrellis *et al*. [14] and Mansouri *et al*. [21] are used Interval Type-2 Fuzzy Logic Algorithm (IT2FLA) that allows for students' preferable means of receiving information requirements as well as a learning approach dependent on students' attributes and engagement levels to provide a tailored learning environment, improving student performance and engagement to calculate the engagement degree of the student. In [12], a Modified Salp Swarm (MSS) algorithm handles fundamental combinatorial optimization issues in engineering and real-world scientific fields and task assignment challenges. Hence, it can be applied to evaluating the student's task-based engagement measures.

1.1. Motivations and Contributions

Enhancing academic performance and learning outcomes requires a dramatic increase in student engagement with higher education. Precision in measuring engagement levels and customising teaching strategies to match students' specific learning needs is lacking in current methodologies. In response to the shortcomings of conventional linear control systems, this study suggests a hybrid approach that combines Adaptive Mamdani Fuzzy Inference System (AMFIS), a PID controller, and the MSS algorithm for optimal engagement. The objective is to provide a responsive system that is always changing based on student input, guaranteeing higher levels of engagement with enhanced assessments, tailored feedback, and enhanced learning experiences.

To act as a roadmap for ongoing improvement of teaching, learning, and student engagement in college education. The study aims to gather data on student's engagement with their academic environment.

- To develop an AMFIS combined with a PID controller and optimized using the MSS algorithm, enabling dynamic adjustments in student engagement based on real-time data and feedback.
- To improve the accuracy and efficiency of student engagement monitoring by implementing a real-time feedback and assessment system, providing personalized feedback through a fuzzy-based decision-making process.
- To enhance key student engagement metrics such as accuracy, reliability, and engagement ratio by validating the proposed model through performance evaluations using metrics like Cronbach's alpha coefficient.

The rest of this research paper is prearranged as follows. Section 2 presents the system model of the proposed AMFIS. The proposed system-based PID controller design using the MSS algorithm is described in section 3. Section 4 validates the numerical analyses of the suggested controller strategy. Finally, section 5 concludes the work and indications for future scope.

2. Related Work

Markopoulos *et al*. [22] created and deployed an Expert System-based software-assisted Fuzzy Logic (ES-FL) on a private college campus. Forty undergraduate students from various nations enrolled in the same course throughout two semesters at the university took part in this research. The technology assesses students' dedication and engagement levels through the co-evolute methodology for knowledge elicitation. This strategy allows college administration to base development analysis on measurable outcomes from the ground up. The results show an improvement in student satisfaction and retention ratio.

Kim [17] created a Colour Fuzzy Framework assisted by Internet of Things (CFF-IoT) method for evaluating the level of student engagement, which gauges students' psychological states by detecting the galvanic skin response wave. To describe the saturation of student engagement levels and enable teachers to give comments to students while keeping an eye on students in actual time. Mobile software on the instructor's phone changes in real-time to match the level of student engagement during class and changes colours. Students who master this method can keep track of their levels of immersion. The results show the assessed outcome level's better Root Mean Square Error (RMSE) value.

Similarly, Kim [16] utilized a thermal infrared envision to assess students' psychological conditions while learning to measure the level of engagement. The area of interest in a class related to temperature information must be collected when the students actively participate in class to make an accurate assessment. Applying the fuzzy theory and temperature model to make small adjustments and provide an RMS waveform based on the fuzzy system is possible.

Einolander *et al*. [11] focused on assessing the key characteristics of student engagement that may be used for student motivation profiles by using the Clustering technique, Fuzzy logic, and Descriptive Statistics (C-F-DS) for describing student engagement. Self-determination, dedication to achieving goals, setting objectives, skill, social integration, and regularity. The data was taken from a life science university with an online questionnaire survey of 242 undergraduate students. A significant correlation was observed between satisfaction and the learning atmosphere (85.7), similar to the current condition (85.3). The students' small sample size prevents the results from being applied to a bigger sample.

Ayouni *et al*. [4] are developing a smart prediction mechanism based on an Artificial Neural Network (ANN) that forecasts students' degree of engagement and then gives them feedback to increase their motivation and commitment. According to their level of engagement, students are divided into three categories: Not engaged, passively engaged, and actively engaged. Based on these findings, the smart prediction mechanism notifies the teacher and gives comments to the students if a student's engagement level declines. The findings show that ML algorithms can forecast a student's degree of engagement with an accuracy of 0.85%, precision of 0.89%, recall of 0.89%, and F1-measure of 0.84%.

Pulido-Luna *et al*. [26] designed an Adaptive Controller based on Mamdani Fuzzy Inference Systems (AC-MFIS) that synchronizes the master and slave system. Fuzzy counterparts of saturation effects produce the input supervision, which serves as the controller's adaptive scheme. A pair of unstable nonhomogeneous independent systems are intended to be synchronized using this control law, which stabilizes the error state using the Lyapunov stability theory. The benefit is optimizing the energy efficiency of the process that causes the system's dynamics. Evaluating the proposed approach's relative performance is challenging because the study does not compare it to other control methods.

Duggal *et al*. [10] used an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to make wise decisions about reward distribution that are directly proportional to the number of coins earned by the students for engagement in college education, which increases the usefulness of the gamified framework. A comparison study is used to validate the suggested gamified framework. The estimated results demonstrated the high level of student engagement in the gamified platform and generated enormous sums of Attendance (ATT) tokens. More than 100 students in 6 distinct classes are testing the gamified framework. The result shows that the accuracy achieved by the ANFIS model is 0.94%, specificity is 0.93%, sensitivity is 0.95%, F1-measure is 0.94%, RMSE is 1.3%, and R^2 is 0.9%.

In [1], the model works based on categorical data with a gradient boost model named the CATboost model, which is based on an ML algorithm that seeks to determine the most effective algorithm for predicting students' engagement in the classroom. To look into how students' performance in a social science class at the open college is affected by their level of engagement. A Virtual Learning Environment (VLE) was used to collect the data, which was then processed using several data pre-processing techniques, including eliminating missing values, standardization, encoded data, and outlier identification. Area Under the Curve (AUC) scores of 0.96%, accuracy of 0.92%, precision of 0.94%, and recall of 100% measures are used to assess the performance of the algorithms.

In [24], educators employ a variety of policies to motivate and encourage pupils to engage and participate actively in a class by using Fuzzy Inference System (FIS) logic to analyze pupils' participation in online classes and, via the use of certain factors, inspire them to connect with lecturers. Analyse learner's engagement in online courses and, using a few key elements, motivate them to engage with professors. Determining students' engagement with this activity by looking at input variables like the overall length, poll results, and discussions. Based on the input criteria, student engagement is divided into active, adequate, and poor. The suggested fuzzy model achieves an accuracy of 0.97%.

Berkay and Demir [6] were constructed 2 Adaptive Fuzzy PID (2AFPID) controllers and powered by optimization algorithms to maintain the output voltage level of the microbial fuel cell at the specified values. It broadens earlier efforts by adjusting fuzzy logic parameters used to tune PID controllers-using methods like Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) techniques. The developed algorithm was put to the test in a variety of scenarios where the reference voltage and load circumstances varied. The outcomes demonstrate that both controllers can successfully control the output voltage by adjusting the fuel flow rate, and these two control techniques work more quickly, effectively, and robustly.

Dey *et al*. [9] introduced a Fuzzy PID controller based on parameter adaption methods for Accurate Monitoring and three-axis Gimbal Stabilisation (FPID-AMGS). The gimbal system's ability to respond to disturbances and varying missile angular rotations is improved. The recommended modified fuzzy PID controller enhances both intermittent and constant-state responses. Compared to the standard PID control technique, the results demonstrate a 41.5% enhancement in tracking performance concerning ISE, a 48% enhancement in control effort, and a 19.5% enhancement in the rejection period of step disturbance.

Aria *et al*. [2] introduced the fuzzy Delphi and fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) for impediments to student engagement. The results classified institutional, environmental, and familial variables as the primary causes, whereas the primary effects were found on the person and family levels. There was a total of 23 sub-factors, 11 of which were considered causes and 12 which were considered effects. The first three were ineffective materials and curriculum, insufficient classroom and institution facilities, and ineffective instructors. First, there was a decline in the quality of the relationships between professors and students; second, there were financial difficulties and excessive tuition costs; and third, the value and standing of education in society were declining.

Liu [20] presented the fuzzy clustering algorithm for designing and implementing an intelligent educational administration system. Fuzzy C-Means (FCM) and Collaborative Filtering (CF) are used in this study to develop a model for predicting students' academic success. In addition to introducing, it to the study of educational administration management, this work also incorporates it into developing a smart educational administration management system. Beginning with a comprehensive explanation of the FCM-CF model. Next, the system's needs and the design's particulars are laid down. The students' predictions about the system's performance are used for later-built simulation trials to evaluate the system's efficacy. A strong correlation exists between students' daily study performances (such as pre-class preparation, classroom performance, attendance, extra-study, and assignment completion) and their overall academic success.

Ge *et al*. [13] offered fuzzy algorithm-based evaluation systems for analyzing the efficacy of International Online Chinese Speaking, Listening, and Teaching. As a result of this technique, Chinese students will be able to evaluate their progress more accurately and objectively and become better at identifying and correcting various sorts of listening and speaking faults. In the same breath, it aids educators in tracking the results of focused pedagogical implementation and making data-driven choices accordingly. Every participant in online Chinese speaking, listening, and teaching can benefit from this hybrid technology, which integrates preexisting language teaching assessment models, utilizes information from online education, and develops corresponding criteria using ML fuzzy algorithms and extensive data sample training, all informed by the theory of efficient teaching assessment.

Chen *et al*. [8] suggested the Multi-Modal Deep Neural Network (MDNN) for Forecasting Learner Engagement via Facial Expression and Gaze Direction in Collaborative Learning (CL). The author of this work used MDNN, which combines facial expression and gaze direction, to foretell students' degrees of participation in group projects. The efficacy of the integrated approach was tested in a live classroom environment. The outcomes verify that the model can reasonably forecast pupils' performance in a group context.

Alam [3] highlighted that Artificial Intelligence (AI) has rapidly changed education teaching and learning. Adaptive learning, smart campuses, teacher evaluation, intelligent tutoring robots, and virtual classrooms use educational AI. AI boosts instructor instruction and student learning. School issues and upgrades must be addressed. Technology is likely to increase AI application in education. The use of AI in education helps instructors and students improve instruction, student learning, and learning styles.

The literature survey highlights various fuzzy logic and AI-based approaches for enhancing student engagement in education. The ES-FL approach was tested on undergraduate students, showing improved satisfaction and retention by assessing dedication using fuzzy logic. The CFF-IoT evaluates student engagement in real-time based on physiological responses, while thermal imaging measures engagement through temperature variations. The C-F-DS approach profiles student motivation, showing correlations between engagement and satisfaction. Additionally, ANFIS and other AI models like CATboost predict student engagement with high accuracy, demonstrating promising results for personalized education solutions.

3. System Model of Proposed Methodology

This section describes the system architecture for an AMFIS model followed by the PID controller using the MSS algorithm.

The measures of student engagement pinpoint crucial components of the educational process that can enhance learning and results like achievements and retention. Educators' expertise and knowledge might be used to design a fuzzy control algorithm to give students a more individualized and efficient learning experience. The inputs and outputs of a fuzzy control system are symbolized by fuzzy sets, characterized by functions known as a membership that gives each of the values in the set a degree of membership. The controller then uses fuzzy rules, determined by the fuzzy sets and the corresponding membership functions, to choose the proper output for a particular input.

The evaluation of state-of-the-art methods for enhancing student engagement through fuzzy control systems reveals various approaches that focus on improving the adaptability and responsiveness of educational systems to student needs. Fuzzy logic systems, such as IT2FLA and fuzzy PID controllers, are used to tailor learning experiences based on student attributes and engagement levels, providing a more personalized educational environment. The MSS algorithm was chosen for its effectiveness in optimizing scaling parameters within fuzzy systems and enhancing the accuracy and efficiency of the fuzzy control system. The MSS algorithm is particularly beneficial in handling non-linearities and uncertainties in educational environments, allowing for dynamic adjustments based on student engagement feedback. It has demonstrated significant improvements in performance metrics, such as tracking accuracy and control effort, compared to traditional methods, making it a robust choice for real-time applications in educational settings.

3.1. System Model

When a mathematical representation of the system to be controlled is either unknown or too complex to make accurate predictions, Fuzzy Logic Control (FLC) is very helpful. The overall system architecture of the proposed model is given in Figure 1. Instead of describing the process quantitatively, FLC strongly emphasizes the actual understanding of the process indication items. The knowledge that underlies FLC is converted into linguistic verbal form. Considering the complexity of fuzzy logic, it appears to be an intriguing technique to inform the teacher of the learning process that should be implemented during college education based on student engagement. Fuzzy sets are used in fuzzy logic to describe linguistic variables.

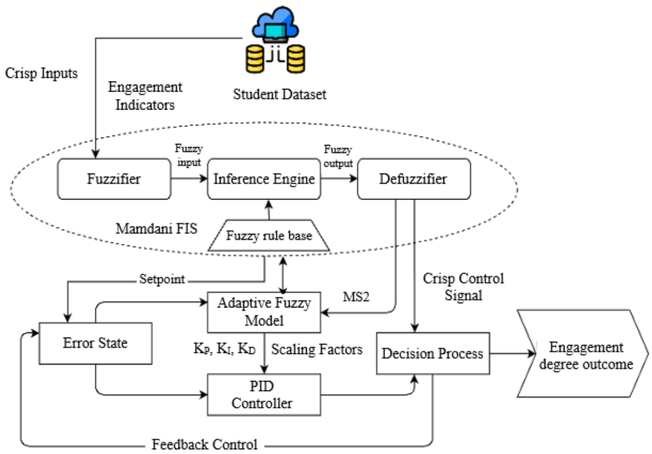


Figure 1. System model of the proposed algorithm.

For each input variable of the student engagement process e multiple categories of indicator responses are defined in a partition that spans every aspect of the discourse. A membership function of engagement process $\mu(e)$ is used to define each group of responses for all 3 categories of students. The student can determine the shape of the membership function, which can be any curve with values between [0, and 1].

Fuzzification, inference, and defuzzification are the three stages of an FLC, as mentioned in Figure 1. The crisp values are transformed into the degree of membership using linguistic variables of fuzzy sets during the fuzzification stage. By encouraging a more individualized and flexible atmosphere for learning, a fuzzy control algorithm may be a helpful tool for enhancing student engagement in college education. Classical sets are often called crisp sets, and their values are crisp in the theory of fuzzy sets.

1. Define input and output variable: consider an input value e as the level of membership in the fuzzy sets will be produced by the fuzzification S_i That can be expressed as $\mu_{S_i}(e)$ where i ranges from i=1, 2, ….., n. The output fuzzy set is created during inference. Trapezoidal Membership Functions (MFs) may represent the steady and imprecise transitioning among fuzzy sets, making them valuable for modelling linguistic parameters in fuzzy control systems. The rule-based system is used to get this set where e is frequently called the discourse universe. It displays the possible range of values for the fuzzy variables, which can be discrete or continuous.

The fuzzy rules are developed by a teacher familiar with student engagement in the course from the experiences of the knowledge base. Since the inference's outcome is likewise a fuzzy set, as mentioned in Figure 1, a conversion to a crisp output value must be performed. During the defuzzification phase of the process, this is done. This method determines the region's centre under the curve, describing the fuzzy final set to determine the crisp value. Relevant scalability parameters for both input and output parameters must be specified to normalize variables between the [0, 1] and [-1, 1] intervals

2. Define the linguistic variable for each engagement indicator: linguistic factors are utilized. For the input variable, the linguistic variable can be represented as {never, sometimes, often, very often}, and the output variable of student engagement is represented as {poor, fair, good, excellent} to describe the many levels or categories for each type of indicator variable. The universes of various linguistic variables can be combined to create MFs with higher dimensions. In fuzzy logic and fuzzy control systems, a type of fuzzy set called a trapezoidal MF is frequently employed. Four factors that describe the membership function's shape are used to define it. The horizontal x-axis signifies the input variable, while the vertical y-axis signifies the degree of membership in the fuzzy set. Four parameters belong to output variables (poor, fair, good, excellent) ⟶ (0, 0.2, 0.8, and 1) that can be used to define the trapezoidal MF for the engagement of students.

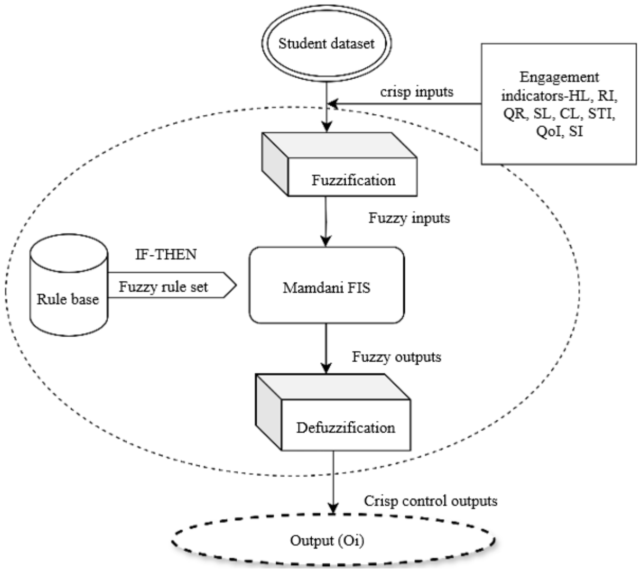


Figure 2. Schematic flow of Mamdani FIS.

3. Fuzzification: using this Mamdani technique drawn

in Figure 2 above, the analogue values of indicator responses are transformed into fuzzy values so that the FLC may use them. A specific set of inputs with appropriate membership functions is chosen for modelling. Triangular membership functions were chosen for this application because of their shape, representation simplicity, and computation speed. Every input variable would be "fuzzified" to produce a variety of potential values. For instance, the input parameter for learning outcomes could be fuzzified into levels like minimum at "poor" and "excellent. at maximum." Assume that the fuzzy controller has multiple inputs to provide context for the entire engagement process by considering two inputs of indicator responses initially and CL_i and HL_i that belongs to the fuzzy closure set S_i and T_i gives the output O_i based on the degree of engagement d_e is calculated by using Equations (1) and (2)

$$\text{if } CL_i \subset S_i \wedge HL_i \subset T_i \text{ then } O_i \subset d_e \tag{1}$$

$$\mu_{S_i}(e) \leq \mu_{T_i}(e) \forall e \tag{2}$$

As shown in Equations (1) and (2), the fuzzy controller entire engagement process, where CL_i represents CL of individual students, HL_i represents the High-order Learning (HL) of each student indicator, μ_{S_i} and μ_{T_i} denotes the membership function of the fuzzy closure set S_i and T_i.

4. Rule base: a set of fuzzy set rules would be established that link the input factors to the coursework's difficulty or pace as the output variable in this scenario. A rule might state that the coursework challenge should be reduced if the student's college educational achievement is poor and their engagement indicators are minimal. The fuzzy controller's inference depends on a rule-based framework, whereby creating a controller and fuzzy control rules (IF-THEN rules) work well. It requires the conditions required for fuzzy control purposes. Each of the aforementioned fuzzy segments (never, sometimes, often, very often) will correlate to a linguistic idea of engagement decision from the teacher during the learning process in college education. The degree of membership of the elements in the fuzzification. It is crucial to ensure the rules are thorough and encompass every possibility of input states when creating fuzzy control rules to increase student engagement. Then, the fuzzy controller can offer each student feedback, difficulties, and assistance depending on their specific requirements, preferences for learning, and degree of engagement. This characteristic of fuzzy control design "completeness" is essential for producing engaging and effective learning opportunities for students. In terms of the number of fuzzy control rules generation, if the input is i, the classification number for the fuzzy rule of each input is k_1, k_2,….k_i is described by using Equation (3). The maximum count of possible levels can be estimated based on indication factors.

$$K_{max} = k_1 k_2 \ldots . k_i \tag{3}$$

The basic idea is to minimize the total amount of fuzzy rules given the completeness threshold to make designing and implementing the fuzzy controller easier. Fuzzy control rules are primarily based on the operator's experience, depending on the criteria for different kinds of effectiveness. The demands of different engagement indicators of performance are frequently mutually exclusive and opposing, making the fuzzy control inconsistent. The control rules are more similar to the logic of teacher expertise by combining systems of fuzzy logic with adaptive management approaches, as well as with professional expertise and linguistic variable selection.

5. As discussed earlier, fuzzification, fuzzy inference, and defuzzification are all steps in the FLC mechanism with necessary inputs from Table 1. The construction of fuzzy rules describes the rule set. However, it is the most crucial element. It specifies the degree of accuracy at which the control activities will be carried out. And may consist of an infinite number of rule sets. The rule base determines the fuzzy controller's accuracy, and numerous rule bases, as feasible, are used by using Equation (4).

$$AMFIS = addRule(MFIS, FuzzyruleList) \tag{4}$$

Rule Base

- **R1**: if students actively engage in classroom discussion, then they are likely to be engaged very often.
- **R2**: if a student submitted their assignment on time, THEN they are likely to be engaged very often.
- **R3**: if a student's assessment performance is poor, THEN they are likely to be never engaged.
- **R4**: if a student requests extra course material to improve learning, THEN they are likely to be engaged sometimes.
- **R5**: if students ask for clarifying doubts during lectures to a teacher, THEN they are likely to be engaged often in Student-Teacher Interaction (STI).

Based on these fuzzy rules, students' engagement regarding indicator responses never, sometimes, often, or very often can be analyzed to calculate the degree of student engagement level.

Mamdani fuzzy inference engine gives the ultimate output value based on various indication parameter response values analyzed from Table 1, which are calculated by the Mamdani system by averaging the degrees of membership of every output value for each rule.

Rule-based system for engagement monitoring with automatic adaptation

IF-THEN rules for engagement classification

- **Rule 1**: if HL is high and STI is high, then engagement level is excellent.

AI adjusts rule thresholds dynamically based on student performance trends.

- **Rule 2**: if CL is moderate and STI is high, then engagement level is good.

Reinforcement learning optimizes CL weight based on feedback.

- **Rule 3**: if HL is low and STI is low, then engagement level is poor.

System recalibrates fuzzy membership functions dynamically to reduce subjectivity.

- **Rule 4**: if Quantitative Reasoning (QR) is high and cl is moderate, then engagement level is fair.

Algorithm modifies thresholds based on peer interaction data.

- **Rule 5**: if HL is low and Reflective Integration (RI) is low, then engagement level is very low.

Self-learning model adjusts engagement weights over time.

- **Rule 6**: if STI is high, CL is high, and HL is high, then engagement Level is maximized.

AI optimizes rule based on LMS activity data and assessment performance

6. Defuzzification: the output variable has to be "defuzzified" to produce a precise value for the degree of difficulty of the course material. The defuzzification process is the last step in the FIS. This process allows one to convert the outcomes as fuzzy sets into numerical values. The centre of gravity, the average of the maximum, and the minimum are extensively utilized as defuzzification approaches. The curriculum in college education could be modified in real-time using this value with Equation (5).

$$O_i = \frac{\int_{i=1}^{max} \mu_{S_i}(e) + \mu_{T_i}(e)}{(UB - LB)} \tag{5}$$

As inferred from Equation (5), where $\mu_{S_i}(e), \mu_{T_i}(e)$ represents the value for the membership function in a fuzzy set at a particular indicator level of student engagement max represents the number of maximum fuzzy rules used in the engagement process. Then, decisions and actions can be made using this clear output value to enhance student involvement in a college education. The resulting crisp value, which can be utilized as a control signal in an adaptive supervisory module system, shows the level of student engagement that the fuzzy system expected.

4. Construction of an AMFIS-based PID Controller Using the MSS Algorithm

Followed by the Mamdani FIS, the proposed model takes input from defuzzification and then generates fuzzy rules for an adaptive fuzzy-based PID controller using MSS that could modify its settings in response to shifts in student engagement, including changes in assessment score, discussion, CL, motivation or attention span, to improve the level of teacher interaction related to feedback given by them. Designing an adaptive fuzzy-based PID controller with a supervisory module that modifies the proportional, integral, and derivative values in response to the controller's performance is one method for engaging students in a college education learning process.

4.1. Adaptive Supervisory Module Design Using MSS Algorithm

A fuzzy logic system with an adaptive supervised module algorithm is a fuzzy control system that utilizes the MSS algorithm to optimize the engagement indicator variables. A single adaptive fuzzy system or a collection of adaptive fuzzy systems can make up an adaptive fuzzy-based PID controller. An "integration factor" is added to the algorithm to compensate for this loss. Specifically, errors, the change in errors, and cumulative errors, the integral of the error over time. The error measures the discrepancy between the desired and actual levels of student engagement. Fuzzy sets with trapezoidal MFs would represent these input variables.

On the other hand, adaptive fuzzy-based PID controllers are a kind of fuzzy controller that may modify its settings in real time based on input from the system. It implies that an adaptive fuzzy controller may adjust to system changes and gradually increase the performance of the fuzzy system model. A typical adaptive fuzzy controller features a learning mechanism that enables it to modify its settings in response to the discrepancy between the expected output and the system's output.

As student engagement levels changed, the Supervisory module would use the MSS algorithm and modify the controller gains K_p, K_i, and K_d of PID controllers.

MSS may also improve the curriculum design or learning environment to increase student engagement. MSS could be used, for instance, to improve the order in which learning activities are completed, the degree of difficulty of the tasks, the feedback system, or the social interaction between students.

1. Initialize the MSS parameters: set the MSS algorithm's parameters, including the sample size, the maximum number of rounds, and the salps' movement-controlling factors, including the weight factors.
2. Initialize the salp locations: Initialize the salp

positions as vectors of the parameters defining the adaptive fuzzy PID controller using Equation (6).

$$Y = (K_p, K_i, K_d, \lambda_1, \lambda_2, \ldots. \lambda_n) \tag{6}$$

As shown in Equation (6), where λ_1, λ_2, ….λ_n represents the scaling factors of the trapezoidal MF that impact the overall form of the resultant fuzzy sets and the amount of overlap between the two fuzzy sets.

$$f(v) = 1 - \rho \tag{7}$$

Where v represents the vectors of the scaling factors of the membership function, ρ is the correlation coefficient between the expected and actual levels of engagement among students, and there is a correlation coefficient using Equations (7) and (8) to calculate the reliability.

$$\rho = \frac{cov(v, w)}{(\sigma_v * \sigma_w)} \tag{8}$$

Here v represents the vectors of the expected levels of learner engagement, w is *the* expected levels of learner engagement, *cov(v,w)* denotes the covariance between v and w, σ_v and σ_w symbolizes the standard deviation of the v and w. The pearson correlation ranges from [-1, +1]. The indication of linguistic values is expressed in Table 1.

Table 1. Pearson correlation of engagement level.

Pearson coefficient (ρ) value	Strength of correlation
-1	Never
-0.8	Very little
-0.6	sometimes
-0.4	Quite a bit
-0.2	Very few times
0	No correlation
0.2	often
0.4	Poor
0.6	Fair
0.8	Good
1	Excellent

The algorithm repeatedly adjusts the relative position of the salps to examine the possible solutions and resolve to a set of expanding factors that gives good control of student engagement. The salps with the greatest fitness values receive greater significance in the search process.

3. Update the position of salp using Equation (9),

$$e_{i(t+1)} = e_{i(t)} + g * R_i * (e_{excellent} - e_{i(t)}) + g * overall(R_{i1} * (e_{0excellent} - e_{i(t)})) \tag{9}$$

Where g represents the non-indicator response variables of engagement in tutorials g_0, discussions g_1 performed during a period t in a classroom. R_i and R_{i1} are the random vectors that deviate the engagement level of students' incomplete assignments and improper reading, $e_{excellent}$ denotes the student's best performance due to higher engagement by doing excessive research projects, volunteer work, and presentations. $e_{0excellent}$ represents the overall excellence of the student's engagement. In each iteration, by using Equation (10), both non-indicator response and random vectors are updated repeatedly,

$$g = g_0 - (g_0 - g_1) * t/T \tag{10}$$

Where t represents the current time representation during the initial iteration, and T represents the total number of iterations.

Constant parameters and abs determine the weights of the variables in the Equations (11) and (12) is the absolute function.

$$R_i = abs(C1 * R_i + C2 * (e_{excellent} - e_{i(t)})) \tag{11}$$

$$R_{i1} = abs(C3 * R_{i1} + C4 * (e_{0excellent} - e_{i(t)})) \tag{12}$$

4. Evaluate the fitness and update the excellent position of student engagement level by using the new fitness value and repeat the steps until indicator response conditions are satisfied. From the salps' determination of the overall optimal position of students' performance, extrapolate the optimized parameter values for the adaptive fuzzy logic-based PID controller in response to the corresponding fuzzy rules obtained from the previous Mamdani FIS.

4.2. Design of Fuzzy-based PID Controller

A Fuzzy-based PID controller replaces the crisp logic output with fuzzy logic. It allows suitable control using linguistic variables, such as poor, fair, good, and excellent, to describe input and output parameters. As the setpoint indicates, the calculation of the expected level of student engagement, which is 90% in the approximation, is given to the error state to maintain the state gain of three parameters. Fuzzification of the error state signal and then applying the set of 5 fuzzy rules generated to determine the appropriate control output of engagement level of the student by using the teacher expert module. The parallel operation can be performed for the Fuzzy Preferability Index (FPI) and Fuzzy PD (FPD) controllers since they share the similar rule base generation described in Figure 2 and are based on five fuzzy rules using Equation (13).

$$K_P(ref(x) - c(x) + K_I \int e(x)dt + K_D\, e(x) \tag{13}$$

Where *ref*(x) indicates the reference error of the input variable, $c(x)$ represents the fuzzy controlled outcome. It can easily identify the change in error rate, tracking error, and error change. As shown in Figure 3, the classroom discussion engagement of students results in an increased number of assessments that can reduce the complexity level of course material in a college education. An expert teacher decision process analyzes these controller information gains. Based on the previous control processes, the college teacher can decide students' engagement degree as poor, fair, good, and excellent and give feedback response to the setpoint. Based on this feedback controller, the teacher can modify the input parameters to fine-tune the indicator responses of engagement levels related to various factors, such as increasing the assessment plans by understanding the students' learning difficulty and improving student engagement in college education.

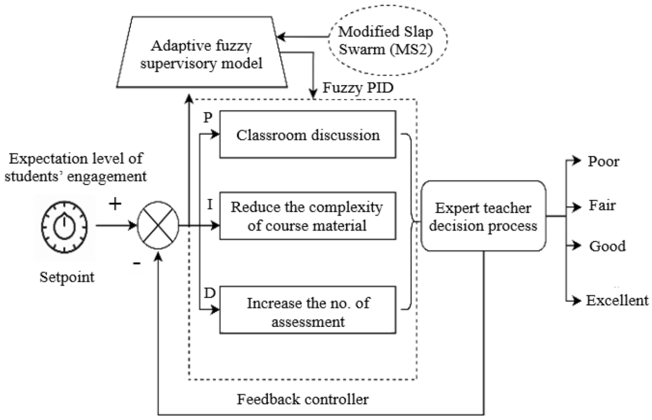


Figure 3. Adaptive fuzzy-based PID controller using MSSA for student engagement.

4.3. Feedback Controller

The feedback controller's input/output variable is identified. In this architecture, the feedback mechanism controller is the two-dimensional fuzzy controller's dual input and output functions mode. This approach can lessen overflow while also ensuring the reliability of control systems. The fuzzy controller chooses the level and indicator of the input/output variable based on the domain of the input variable. Based on the expert decisions and analyzing the factors from Table 2, the degree of student engagement level can be calculated.

Table 2. Range of student engagement indicators.

Function	Indicator variables	The fuzzy rule set with range [0-60]
Input	HL	Never [0-9] Sometimes [10-29] Often [30-49] very often [50-60]
	RI	
	QR	
	SL	
	CL	
	STI	
	QoI	
	SI	
Mamdani FIS	Student degree of engagement level	Poor [0-14] Fair [15-29] Good [30-44] Excellent [45-60]

The summary of the proposed AMFIS-PID-MSS algorithm is used to adjust the membership functions of the FIS in real-time, and better controlling of student engagement in college education indicators can be achieved. The AMFIS gets the input from the linguistic variables of the engagement level of students based on their trapezoidal MF and gives the degree of engagement in a classroom. The fuzzy PID controller gets the defuzzification output and changes the parameters automatically in response to the error rate and feedback controller from the teachers' decision process. In the supervisory module, the heuristic MSS algorithm optimizes the parameters of fuzzy rules and promotes students' reliable engagement level in college education.

A pilot study or collaboration with a university or classroom had been planned to test the fuzzy control algorithm in a live classroom environment. This approach aimed to demonstrate the model's ability to handle practical challenges and provide direct insights into its performance in a real educational context, which would further validate the findings from simulations and open-source data.

5. Numerical Analysis

The numerical evaluation of the recommended fuzzy approach for student engagement is described in this section.

5.1. Data Acquisition and Description

The survey of student engagement belonging to Irish was created to support and promote quality improvement. Many facets of students' experiences in higher education are reflected in [15]. It is intended to strongly emphasize student engagement, including how much time and effort students contribute to worthwhile learning opportunities and how much colleges support their engagement in such activities. Indication scores are computed on a rating system ranging from 0 to 60 with a detailed description given in [27] utilizing the answers to the participating subject questionnaire items.

Indication score (all respondents) HL-33, Reflective with a ratio of Integration (RI)-27, QR-19, Strategy of Learning (SL)-31, CL-25, STI 10, Quality of Interactions (QoI)-36, Support Environment (SE)-24. As discussed above, the scores possessed with various responsive functions are very little, some, quite a bit, and very much. The linguistic variables are scaled from 1 to 7, with 1 as a poor response and 7 as an excellent response.

5.2. Analysis of Results

The outcomes of the suggested fuzzy-based algorithm and the FIS analysis model's performance indicators for student engagement level are examined in this part.

1. Analysis of Cronbach's alpha reliability. When evaluating the reliability of a group of non-indicator item responses or questions in a survey or test, the chance of frequently utilizing Cronbach's alpha is a measure of internal reliability consistency. It can be used to evaluate the accuracy of systems based on fuzzy logic that evaluates student engagement. The Cronbach's alpha coefficient is calculated by using Equation (14) as follows:

$$\alpha = \left(\frac{ni}{ni-1}\right) * (1 - \left(\sum (variance\ of\ each\ ni\ item\ /\ total\ variance)\right) \tag{14}$$

Where a group of non-indicator item responses or questions in a survey or test is indicated by $n\,i$, the total of each non-indicator item deviation is represented as Σ followed by the total variation on the engagement indicator survey or test for all types of students' category mentioned.

Figure 4 shows that Cronbach's α reliability measure is identified based on the number of indicator responses generated from the open-source dataset [27]. Here, the coefficient ranges from 0 to 1. The items consistently measure the same student engagement when the reliability value for internal consistency is 0.7 and greater than that. Whereas values beyond 0.8 are regarded as good and above 0.9 to be outstanding. This measure shows that indicators like HL, STI, and QoL are comparatively higher than others. Identifying the non-indicator items or questions used to gauge student engagement is necessary to determine Cronbach's alpha for a fuzzy logic-based system. Once the set of items has been determined, gather information from students who have utilized the fuzzy control system and grade the non-indicator items or questions following the level of engagement by each student in the three categories.

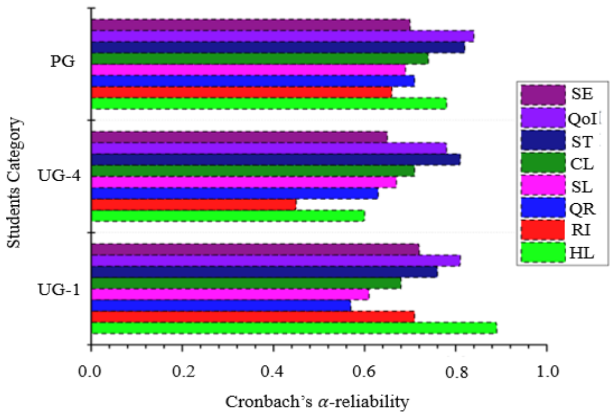


Figure 4. Cronbach's alpha reliability based on engagement indicators.

2. Accuracy comparison. True Positive (TP): when a student was genuinely engaged, the proposed algorithm accurately recognized the student as such. False Positive (FP): when the suggested algorithm mistakenly identified students as engaged when not engaged. True Negative (TN): when the suggested algorithm properly identified students as not engaged when they were not. False Negative: when a student was actually engaged, but our algorithm mistakenly thought they weren't.

Figure 5 illustrates the accuracy comparison of the proposed method with existing algorithms, in which the proposed model demonstrates a higher expected level of student engagement based on the parameters: Poor, Fair, Good, and Excellent, calculated using Equation (15). With the help of the membership function, the linguistic variables and the indicator response of engagement are varied for different criteria like HL. It analyzes the students understanding level and practical problem-solving. For STI, it analyzes the career plans, student groups, and course topics. For SE, it analyzes non-academic responsibilities and academic performance. The main reason for improving student engagement level is by adjusting the fuzzy rule set based on IF-THEN and decision feedback from teachers based on experience.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{15}$$

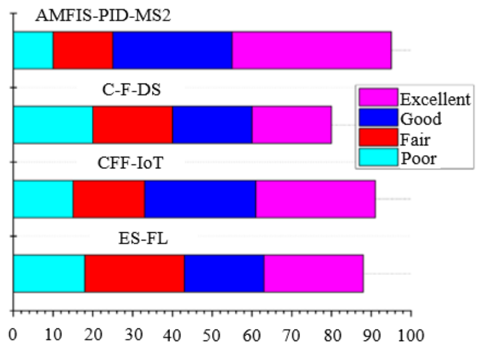


Figure 5. Accuracy comparison.

3. Membership Function for indicator variables. As shown in Figure 6, the trapezoidal MF ranges from 0 to 1. Four engagement indicators are categorized based on the student engagement level in the classroom by analyzing the input variables of indicators and non-indicators inside the variables. Every indicator is analyzed, especially in the fuzzy-based PID controller. The setpoint is fixed to calculate the engagement level of indicators based on automatic adjustment of the fuzzy rule set generated using AMFIS with a level of 0 to 60.

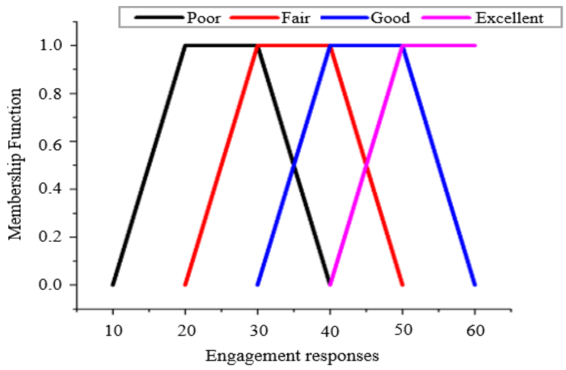


Figure 6. Membership function for indicator variables factors.

4. Engagement Ratio (%). From Figure 7, the graph results show the degree of engagement level of students based on the teacher feedback process taken from the PID control by analyzing the various indicator responses from [19]. The engagement results are optimized with the MSS meta-heuristic algorithm by identifying the weights of the indicator values. Here, the proposed method's engagement level is higher than other ES-FL, CFF-IoT, and C-F-DS approaches. These indicators included classroom discussion, team meetings, research work contribution, assessment completion, and grade score calculation in response to student and teacher interaction. The adaptive fuzzy PID controller module analyzes student engagement if it does not meet the expected setpoint. The feedback response

comments on the MSS algorithm. It optimizes the engagement response based on the teacher's decision process.

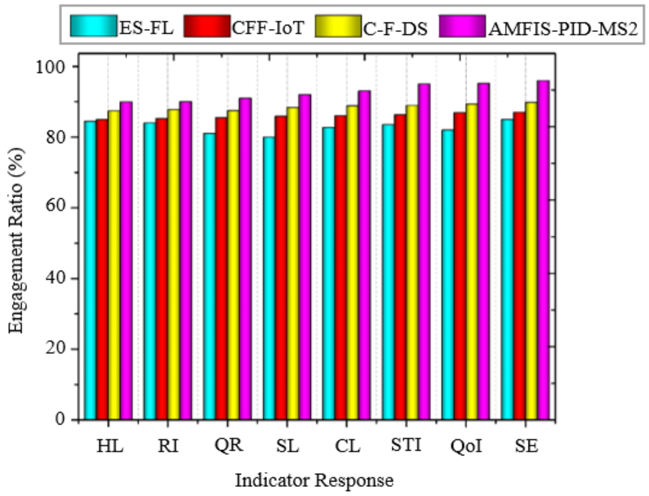


Figure 7. Comparison of engagement ratio.

5. RMSE: Equation (16) helps to update the difference in the engaged level of student ratio in a college classroom.

$$RMSE = \sqrt{sum\left(\frac{(OBSERVED\ VALUE - SETPOINT\ VALUE)^2}{N}\right)} \quad (16)$$

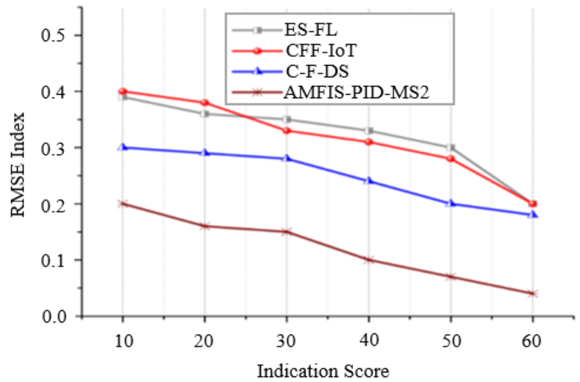


Figure 8. RMSE index comparison.

As shown in Figure 8, the error rate control from the proposed algorithm shows a minimal error rate compared to other approaches based on the three error gain indicators obtained from Equation (6). Here, the indication score represents the engagement criteria of students concerning various parameters taken from [3]. Based on the automatic update of the error state and change in error gain with scaling parameters of the expert decision process, the feedback is passed through the controller, and the error state is updated concerning the setpoint. The obtained engaged level of each indicator is compared with the setpoint value to check the error difference using integral parameters, and the final update gives the minimal difference between them.

Comparing this novel approach to earlier research, it performed better. Teachers and school administrators can utilize the suggested approach to determine whether students are engaged fully or not.

6. Sensitivity analysis of membership functions. An equation representing the effect of membership function parameters and fuzzy control parameters on system performance can solve the absence of sensitivity analysis. Modelling system performance with a simplified Equation (17):

$$P_{sys} = \sum_{i=1}^{n} w_i \cdot \mu_i(e) \quad (17)$$

In Equation (17), P_{sys} is the overall system performance. w_i represents the weights of different engagement indicators. $\mu_i(e)$ represents the membership function of the engagement indicator, e.

Table 3 demonstrates how varying the membership functions affects performance metrics like error rates and engagement ratios, providing a clear sensitivity analysis.

Table 3. Different parameter values affect error rates or engagement outcomes.

Parameter	**Low value (0.2)**	**Medium value (0.5)**	**High value (0.8)**
Error rate (%)	12%	8%	5%
Engagement ratio (%)	60%	75%	90%

7. Comparison with more recent AI-enhanced models. The proposed approach is compared to AI-enhanced educational systems Knewton, CFF-IoT, and C-F-DS to highlight features, learning techniques, adaptability, and variations in strengths.

Table 4. Comparison with more recent AI-enhanced models.

Model	**Features**	**Learning method**	**Adaptation**	**Comparison parameter**	**Strengths**	**Weaknesses**
Proposed algorithm (fuzzy control)	fuzzy logic, optimized with MSS	Adaptive Mamdani fuzzy System	Real-time updates with student engagement feedback	Engagement, error rates	Customizable, handles non-linearity	Sensitive to parameter changes
Knewton	Adaptive learning platform	AI and data analytics	Curriculum customization	Learning efficiency	Widely adopted, scalable	Limited real-time engagement
CFF-IoT	IoT-based color engagement system	Machine learning and IoT	Real-time feedback	Engagement level	Real-time engagement monitoring	Lacks depth in curriculum adaptation
C-F-DS	Descriptive statistics and fuzzy logic	Clustering, statistical analysis	Adaptation based on student profiles	Motivation	Simple design, easy implementation	Misses adaptive real-time adjustments

The fuzzy control algorithm is compared against Knewton, CFF-IoT, and C-F-DS AI-enhanced educational models in Table 4. Fuzzy logic and real-time feedback optimize student engagement and error rates, making the model highly customisable and non-linearity-resistant. It is sensitive to parameter changes.

With great scalability but limited real-time engagement tracking, Knewton emphasises curriculum customisation for learning efficiency. CFF-IoT excels in real-time monitoring but lacks curricular depth, while C-F-DS offers simple statistical learning but no adaptive real-time modifications.

Table 5 compares the limitations of traditional expert-defined fuzzy rules, the enhancements introduced by AMFIS-PID with MSS optimization, and potential future improvements using AI-driven fuzzy rule adaptation. It highlights key aspects such as automation, adaptability, error handling, and feedback mechanisms, providing a clear view of the progression toward more efficient and intelligent engagement assessment models.

Table 5. Comparison of expert-defined fuzzy rules, AMFIS-PID with MSS, and future AI-based optimization.

Aspect	Expert-defined fuzzy rules	AMFIS-PID with MSS optimization	Future AI-based optimization
Rule definition	Manual, expert-driven	Optimized via MSS algorithm	AI-driven fuzzy rule learning
Subjectivity	High	Reduced	Eliminated with data-driven AI
Consistency	Varies by institution	Improved via optimization	Fully stable across contexts
Adaptability	Limited manual updates	Automatic tuning via MSS	Fully adaptive with ML models
Automation	None	Partial (feedback-based)	Fully autonomous optimization
Generalizability	Low	Higher (adaptive scaling)	High (self-learning system)
Error handling	Rigid rules, higher errors	Improved accuracy via MSS	AI reduces errors dynamically
Feedback	Manual refinement needed	Real-time feedback loop	AI-driven automatic feedback

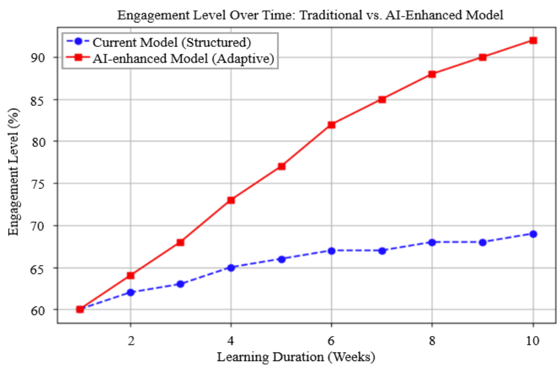


Figure 9. Engagement level over time-traditional vs. AI-enhanced model.

Figure 9 compares a structured fuzzy-based engagement model with an AI-enhanced personalized learning model. The structured model assumes uniform learning patterns, leading to a gradual increase in engagement. In contrast, the AI-driven model dynamically adapts to individual learning styles, cognitive abilities, and motivation levels, resulting in higher and sustained engagement. This highlights the potential of AI-driven recommendations in tailoring learning experiences. Implementing adaptive learning techniques would enhance the model's applicability to diverse learners, enabling real-time adjustments for optimized engagement and improved learning outcomes.

Higher-order learning, student-teacher interaction, and CL were effective engagement measures in the study. However, modern education incorporates project-based, experiential, and competency-based learning models that require a more flexible engagement evaluation framework. Expanding the model with adaptive engagement metrics and real-time learning analytics would enhance its applicability to non-traditional settings. Integrating AI-driven analytics and machine learning-based engagement tracking could further improve adaptability, ensuring a comprehensive and dynamic assessment across diverse educational methodologies while maintaining accuracy and responsiveness to evolving learning environments.

Enhancing student engagement requires personalized learning experiences that adapt to individual learning styles, cognitive abilities, and motivation levels. The proposed model can evolve beyond traditional engagement monitoring by integrating AI-driven adaptive learning, real-time analytics, and personalized feedback. Future advancements will enable dynamic content delivery, ensuring higher retention, motivation, and improved academic outcomes in diverse educational settings.

The model successfully utilized predefined engagement indicators, providing a structured and data-driven approach to monitoring student participation. To enhance its applicability in modern, non-traditional learning environments, future advancements can integrate AI-driven analytics and machine learning models to capture behavioral, emotional, and cognitive engagement metrics. The system can dynamically adjust to project-based, experiential, and competency-based learning models by incorporating real-time engagement tracking and adaptive learning frameworks. These enhancements would further improve the model's flexibility, ensuring comprehensive engagement assessment across diverse educational settings while supporting personalized and adaptive learning experiences.

6. Conclusions

Higher-order learning and STI were important indications of the relationship between student engagement and academic achievement, suggesting that successful students actively participate in these activities and positively interact with teachers. Therefore, HL and STI should be prioritized by schools as learning interventions to boost student performance. The proposed model is well-suited for controlling systems with non-linearities, uncertainties, and changing dynamics due to its ability to adapt to changing feedback responses to student engagement conditions by continuously updating its parameters by teachers. The suggested method enhanced student engagement and learning outcomes. The system may build rules based on student responses and expert teacher knowledge, enabling an expert decision-making process that can adjust to the demands of specific students using fuzzy logic. Using the MSS algorithm, the scaling parameters of the membership functions are optimized, significantly enhancing the system's accuracy and efficiency. The future scope of the suggested strategy can be used in real-time learning environments such as educational websites, intelligent classrooms, etc. Students can receive quick feedback from this implementation, which can also assist them in determining their strengths and limitations. In any academic application, the proposed approach can be used to calculate student engagement levels in a classroom.

References

[1] Alruwais N. and Zakariah M., "Student-Engagement Detection in Classroom Using Machine Learning Algorithm," *Electronics*, vol. 12, no. 3, pp. 1-29, 2023. https://doi.org/10.3390/electronics12030731

[2] Aria A., Jafari P., and Behifar M., "The Impediments to Student Engagement: A Hybrid Method Based on Fuzzy Delphi and Fuzzy DEMATEL," *World Journal of Education*, vol. 10, no. 5, pp. 45-60, 2020. https://doi.org/10.5430/wje.v10n5p45

[3] Alam A., *Advanced Computing and Intelligent Technologies*, Springer, 2022. https://doi.org/10.1007/978-981-19-2980-9_32

[4] Ayouni S., Hajjej F., Maddeh M., and Al-Otaibi S., "A New ML-based Approach to Enhance Student Engagement in an Online Environment," *PloS ONE*, vol. 16, no. 11, pp. 1-16, 2021. https://doi.org/10.1371/journal.pone.0258788

[5] Balachandran L., Chang-Koh S., and Selvarajan S., *Student Growth and Development in New Higher Education Learning Spaces*, Routledge, 2022. https://doi.org/10.4324/9781003212843

[6] Berkay E. and Demir M., "Design of Intelligence-Based Optimized Adaptive Fuzzy PID Controllers for a Two-Chamber Microbial Fuel Cell," *Asia-Pacific Journal of Chemical Engineering*, vol. 18, no. 2, pp. e2867, 2022. https://doi.org/10.1002/apj.2867

[7] Bond M., "Facilitating Student Engagement through the Flipped Learning Approach in K-12: A Systematic Review," *Computers and Education*, vol. 151, pp. 103819, 2020. https://doi.org/10.1016/j.compedu.2020.103819

[8] Chen Y., Zhou J., Gao Q., Gao J., and Zhang W., "MDNN: Predicting Student Engagement via Gaze Direction and Facial Expression in Collaborative Learning," *CMES-Computer Modeling in Engineering and Sciences*, vol. 136, no. 1, pp. 381-401, 2023. DOI:10.32604/cmes.2023.023234

[9] Dey S., Kumar T., Ashok S., and Shome S., "Design of Adaptive Fuzzy PID Control Framework for 3-Axis Platform Stabilization," *in Proceedings of the International Conference on Power, Instrumentation, Energy and Control*, Aligarh, pp. 1-6, 2023. DOI:10.1109/PIECON56912.2023

[10] Duggal K., Gupta L., and Singh P., "Gamification and Machine Learning Inspired Approach for Classroom Engagement and Learning," *Mathematical Problems in Engineering*, vol. 2021, pp. 1-18, 2021. https://doi.org/10.1155/2021/9922775

[11] Einolander J., Vanharanta H., Mądra-Sawicka M., Paliszkiewicz J., Kantola J., and Pietrzak P., "Evaluating and Profiling Student Engagement and Motivation at a Higher Education Institution," *European Research Studies*, vol. 24, pp. 610-625, 2021. DOI:10.35808/ersj/2754

[12] El-Ashmawi W. and Ali A., "A Modified Salp Swarm Algorithm for the Task Assignment Problem," *Applied Soft Computing*, vol. 94, pp. 106445, 2020. https://doi.org/10.1016/j.asoc.2020.106445

[13] Ge D., Wang T., Qi C., and He S., "Design of a Fuzzy Algorithm-based Evaluation System for the Effectiveness of International Online Chinese Listening and Speaking Teaching," *BioMed Research International*, vol. 3, pp. 1-7, 2022. DOI:10.1155/2022/8135282

[14] Iatrellis O., Stamatiadis E., Samaras N., Panagiotakopoulos T., and Fitsilis P., "An Intelligent Expert System for Academic Advising Utilizing Fuzzy Logic and Semantic Web Technologies for Smart Cities Education," *Journal of Computers in Education*, vol. 10, no. 2, pp. 293-323, 2023. https://doi.org/10.1007/s40692-022-00232-0

[15] ISSDA|Irish Survey of Student Engagement. 2024. StudentSurvey.ie (Irish Survey of Student Engagement) 2023. [dataset]. Version 1. Irish Social Science Data Archive. SN: 0030-10, https://www.ucd.ie/issda/data/studentsurveyie/studentsurveyie2023/, Last Visited, 2024.

[16] Kim P., "Ambient Intelligence in a Smart Classroom for Assessing Students' Engagement Levels," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 10, pp. 3847-3852, 2019. DOI:10.1007/s12652-018-1077-8

[17] Kim P., "Real-Time Bio-Signal-Processing of Students Based on an Intelligent Algorithm for Internet of Things to Assess Engagement Levels in a Classroom," *Future Generation Computer Systems*, vol. 86, pp. 716-722, 2018. https://doi.org/10.1016/j.future.2018.04.093

[18] Krouska A., Troussas C., Voulodimos A., and

Sgouropoulou C., "A 2-Tier Fuzzy Control System for Grade Adjustment Based on Students' Social Interactions," *Expert Systems with Applications*, vol. 203, pp. 117503, 2022. https://doi.org/10.1016/j.eswa.2022.117503

[19] Li J., Li Y., and Han L., "Constitutive Artificial Neural Network for the Construction of an English Multimodal Corpus," *The International Arab Journal of Information Technology*, vol. 22, no. 2, pp. 398-409, 2025. https://doi.org/10.34028/iajit/22/2/15

[20] Liu F., "Design and Implementation of Intelligent Educational Administration System Using a Fuzzy Clustering Algorithm," *Scientific Programming*, vol. 2021, pp. 1-14, 2021. https://doi.org/10.1155/2021/9485654

[21] Mansouri T., ZareRavasan A., and Ashrafi A., "A Learning Fuzzy Cognitive Map (LFCM) Approach to Predict Student Performance," *Journal of Information Technology Education: Research*, vol. 20, pp. 221-243, 2021. https://doi.org/10.28945/4760

[22] Markopoulos E., Einolander J., Vanharanta H., Kantola J., and Sivula A., "Measuring Student Engagement and Commitment on Private Academic Institutions Using Fuzzy Logic Expert System Metrics Applications," *in Proceedings of the International Conference on Human Factors in Training, Education, and Learning*, Washington (DC), pp. 163-173, 2020. https://doi.org/10.1007/978-3-030-20135-7_16

[23] Morton K. and Carroll M., "An Autonomous E-Learning Discussion Facilitator: A Novel Approach," *International Journal for Educational Media and Technology*, vol. 15, no. 2, pp. 78-86, 2021. https://ijemt.org/index.php/journal/article/view/10

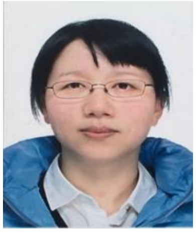
[24] Nagothu S., Sri P., and Koppolu R., "Smart Student Participation Assessment Using Fuzzy Logic," *in Proceedings of the International Conference on Computational Intelligence and Sustainable Technologies*, Warangal, pp. 673-685, 2022. https://doi.org/10.1007/978-981-16-6893-7_59

[25] Nkomo L., Daniel B., and Butson R., "Synthesis of Student Engagement with Digital Technologies: A Systematic Literature Review," *International Journal of Educational Technology in Higher Education*, vol. 18, no. 34, pp. 1-26, 2021. https://doi.org/10.1186/s41239-021-00270-1

[26] Pulido-Luna J., Lopez-Renteria J., and Cazarez-Castro N., "Mamdani-Type Fuzzy-based Adaptive Nonhomogeneous Synchronization," *Complexity*, vol. 2021, pp. 1-11, 2021. https://doi.org/10.1371/journal.pone.0258788

[27] StudentSurvey.ie, Irish Survey of Student Engagement, Institute of Technology, Sligo, Results of StudentSurvey.ie 2020, https://studentsurvey.ie/sites/default/files/users/user27/StudentSurvey.ie_2020_IT%20Sligo.pdf, Last Visited, 2024.

[28] Tarosh J. and Centofanti S., "Effectiveness of H5P in Improving Student Learning Outcomes in an Online Tertiary Education Setting," *Journal of Computing in Higher Education*, vol. 36, no. 2, pp. 469-485, 2024. https://doi.org/10.1007/s12528-023-09361-6



Yan Chen has a Master Degree in Science, Research Associate. Graduated from the Chengdu College of Technology in 1998. Worked in Chengdu University of Technology. Her research interests include Reformation of Talent-Training Mode and Quality Guarantee System of Talent Cultivation.