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Course Content and Learner Classification using Fuzzy Logic to Enhance Adaptive Learning System

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ABSTRACT

Adaptive learning systems aim to personalize the learning experience based on individual learner characteristics. These systems can enhance student engagement and improve learning outcomes by tailoring course content to meet each learner's needs. However, the challenge lies in accurately classifying learners and adjusting course materials accordingly. This paper proposes a method for learner classification and course content adaptation using fuzzy logic. By implementing fuzzy logic, the adaptive learning system can categorize learners more precisely based on parameters such as prior knowledge, educational background, and engagement levels. The proposed model enhances the effectiveness of adaptive learning systems by delivering customized learning experiences. Experimental results demonstrate the effectiveness of this approach in optimizing course content and improving learner satisfaction.

KEYWORDS

Adaptive e-learning, behavior parameter, assessment, level of knowledge, learning material, fuzzy logic etc.

Introduction

In the era of digital education, adaptive learning systems have become pivotal in offering personalized learning experiences. Traditional approaches often rely on a "one-size-fits-all" model, which does not account for the diverse needs and learning paces of individual students. Adaptive learning systems [1] aim to address this by tailoring educational content to each student's needs. Fuzzy logic, known for its ability to handle uncertainty and imprecision, can play a crucial role in learner classification and course content adaptation [2]. This paper focuses on the application of fuzzy logic in enhancing adaptive learning systems by classifying learners and adjusting course content based on their characteristics.

Web-based learning environments [3] enable students to gain knowledge anytime, anywhere. E-learning can provide the maximum number of participants with diverse teaching styles, preferences, and needs. The primary goal of learning is to create e-learning environments that cater to learner requirements. An effective system should evaluate each learner's level using a course material selection algorithm that considers specific needs [4].

The significance of these systems has been further emphasized during pandemic times, as they can support IT and IS instructors in reimagining and modifying their course-learning designs. This capability enables educators to provide students with more enriching and impactful learning experiences [2]. As a result, an adaptive e-learning system is being developed to deliver learning materials based on the individual needs and comprehension abilities of each student.

Adaptive e-learning parameters for describing student and learner processes [5] include behavioral personal preferences, subject knowledge, goals, qualification, age, likes, dislikes, and quiz/test performance. The student model is typically represented as a profile that contains personal preferences that machines can process directly. Various research methods differ in their approaches to representing student profiles, maintaining up-to-date student models, and strategies for providing personalized data [6].

This study highlights the importance of implementing adaptive intelligence-based e-learning platforms in the educational environment. The researchers anticipate that their findings will offer valuable insights to both practitioners and scholars regarding adaptive e-learning systems, particularly regarding how these systems are employed to tackle various challenges encountered by students who utilize them. The rest of the paper is structured as follows: section-3 discusses the methodology of an adaptive intelligent learning and evaluation system, section-4 covers the implementation of the system described in section-3, section-5 examines the performance evaluation of the proposed system, and section-6 concludes with summary and future work directions.

1. Background and Related Work

1.1 Adaptive Learning Systems

Adaptive learning systems modify the content delivered to a learner based on their learning behavior and performance [7]. These systems analyze data such as quiz results, time spent on tasks, and interaction patterns to adapt the learning path. Existing adaptive learning models primarily use rule-based or machine-learning approaches for content adaptation. However, these models often struggle with the ambiguity inherent in assessing learners' cognitive abilities and engagement levels [8].

1.2 Fuzzy Logic

Fuzzy logic is a mathematical approach that deals with reasoning that is approximate rather than fixed and exact. Unlike binary logic, which categorizes inputs into distinct classes, fuzzy logic allows for a degree of membership in multiple classes [9-10]. This makes it particularly useful in situations where data is uncertain or imprecise. Fuzzy logic has been applied successfully in areas like control systems, medical diagnostics, and decision-making processes, where the precise measurement of parameters is difficult.

1.3 Application of Fuzzy Logic in Education

Recent research has explored the use of fuzzy logic in educational settings for learner evaluation, course recommendation, and adaptive assessments. These applications have shown that fuzzy logic can effectively model the uncertainty and subjectivity involved in educational data. However, the specific use of fuzzy logic for learner classification and course content adaptation remains underexplored.

Users' knowledge level has been the focus of most adaptation efforts in this field [11-12]. Other learner characteristics include background, experience with hyperspace, preferences, and interests [12]. Learning styles and their influence on academic achievement have received insufficient attention. Although learning styles are valuable for enhancing individual learning, as noted by [13], statistics show that students' learning styles play a vital role in improving online teaching and e-learning performance, as highlighted by [14], while taking student education into account.

Another crucial aspect is the evaluation of how adapting to students' teaching styles affects their performance. Authors in [15] developed an adaptive learning system utilizing a fuzzy-clustering approach. A student model was created by analyzing the Weblog data to identify relevant terms on the visited pages. In this instance, a Fuzzy Clustering Approach and Statistical K-means clustering technique were employed to predict students' interest in providing Semantic Web learning content. Researchers in [16] examined adaptive e-learning hypermedia, focusing on learning style as an adaptation mechanism, and discovered that out of ten systems, six did not appear to publish qualitative evaluations.

To explore the effectiveness parameters of e-learning based on content, a method should be established that adapts to individual Learning Styles and tailors the experience to each student [18-19]. Adaptive knowledge-based technology has been utilized to enhance the learning process by adjusting the course content to align with students' learning styles.

2. Methodology of Adaptive Learning and Evaluation System

The proposed system consists of three primary modules:

2.1 Data Collection Module

Gathering information about students, including their existing knowledge, educational history, and level of involvement to design system [11] is highlighted the idea of adaptive systems, concentrating on improving web-based education by offering an Adaptive and Intelligent Web-Based Educational System (AIWBES) as an alternative to traditional approaches. The primary aim of the proposed Adaptive Intelligent Learning and Evaluation System (AILES) is to focus on student data that present learning materials based on behavioral factors such as age, education, knowledge level, preferences, objectives, plans, and personal interests. Accomplishing these goals depends heavily on ensuring the proper operation of an adaptive learning system that explicitly maintains and updates students' characteristics, preferences, and feature plans. These data are used by an adaptive learning system to enable adaptability. The e-learning and assessment system is proposed as an Adaptive Intelligent Learning and Evaluation System (AILES), which functions as a domain engine that allows students to learn course materials according to their knowledge level. Students initially provided information such as name, email address, age, qualifications, and course (x1, x2,....,xn).

As illustrated in Figure-1, offers three categories of course material: basic, moderate, and advanced. This system automatically chooses the appropriate course material for students based on their behavioral performance and knowledge level. These factors were determined using a fuzzy-based course-material selector (FBCMS). The FBCMS uses three parameters: age (A), qualification (Q), and subject knowledge (S). The learner directly enters the age and qualifications during registration. Subject knowledge was assessed using a multiple-choice test on selected subjects. The proposed system administered an online test with a maximum score of 60 points. The test consisted of 20 questions, each worth three marks. In this test with negative marking, one mark was deducted from the obtained marks for each incorrect answer. The test result, known as subject knowledge (S), scored out of 60.

The system inputs these three parameters into a fuzzy-based controller to evaluate the behavioral performance and knowledge level. Based on this assessment, the system automatically selects appropriate teaching course materials. The FBCMS is further elaborated in the Design and implementation section of the AILES.

2.2 Fuzzy Classification Module

Fuzzy logic is used to classify learners based on the collected data. To develop an algorithm for finding the behavior index for each learner using fuzzy logic, we need to define the parameters, linguistic variables, fuzzy

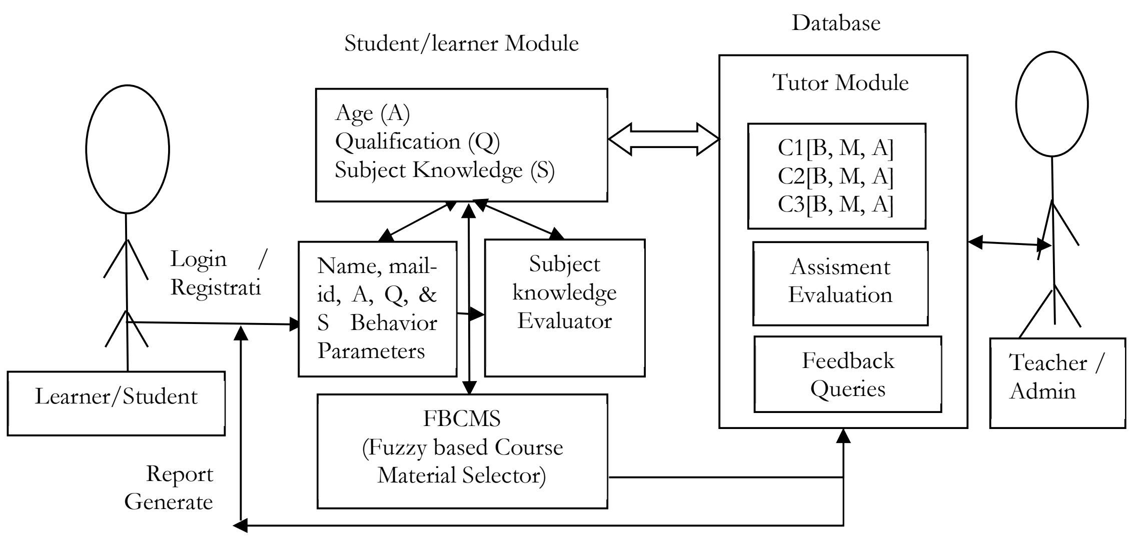


Figure-1 Adaptive Intelligent Learning and Evaluation System (C1, C2, C3 different Courses, B – Basic Course Material, M – Moderate Course Material, A – Advance Course Material.)

sets, rules, and inference mechanisms. We discuss the following

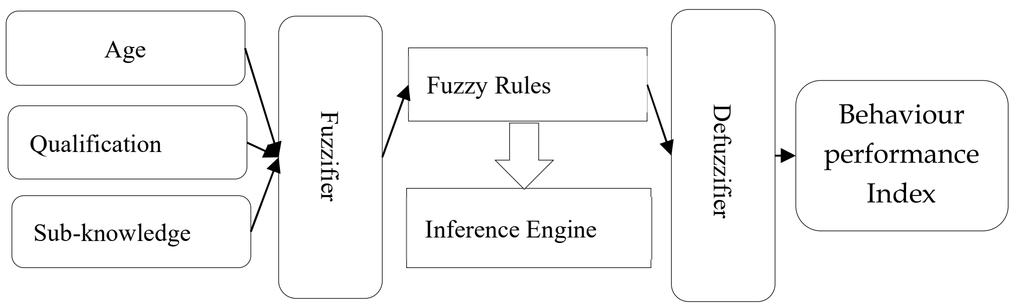
3.2.1. Define Input and Output Variables

- Input Variables of Behavior index:
  i) Age (A) ii) Qualification (Q)
  iii) Subject Knowledge (S)
- Output Variable:
  i) Behavior Performance Index (BI)

3.2.2. Design of Fuzzy Controller – FBCMS

The Fuzzy Based Course Material Selector (FBCMS) is a fuzzy controller created to choose the level of behavior performance index, as illustrated in Figure-2. It takes Age, Qualification, and subject knowledge as inputs, and produces the behavior performance index level as the output. The level selector consists of four main components: fuzzifier, fuzzy rule base, inference engine, and defuzzifier. The fuzzifier uses fuzzy logic to convert numerical input values into fuzzy categories such as low, average, and high. The input from the fuzzifier was processed by the inference engine, which applied fuzzy rules to generate a fuzzy performance selection index. The proposed FBCMS fuzzy controller has twenty-seven fuzzy rules. The defuzzifier then transforms the fuzzy selection index into a behavior performance index, which is presented as the as the output.

Unlike AIWBES [11] and adaptive e-learning systems based on the semantic web and fuzzy clustering [12], which consider learner features such as background, hyperspace experience, preferences, and interests as an alternative to conventional systems, the proposed system utilizes three input parameters: age, qualification, and subject knowledge. The limitations of AIWBES and other traditional systems, including the "One size fits all" approach, have been addressed previously, along with the rationale for selecting the proposed input parameters. The objective of the system is to provide tailored learning materials based on learners' behavioral performance levels, rather than offering identical content to all users.



Age directly impacts the behavior performance index and indirectly affects the knowledge level. Low-age learners have low learning capability or performance; medium-age learners demonstrate average capability, and high-age learner's exhibit high capability.

Qualification, the second input parameter, showed a positive correlation between higher qualifications and an increased behavior performance index. Students with HSC (11th to 12th class) qualifications had lower knowledge and a low behavior performance index. Those with UG (13-15 Class) qualifications possessed average knowledge and an average behavior index, while PG and PG plus (16 above Class) students demonstrated higher knowledge and a high behavior value index.

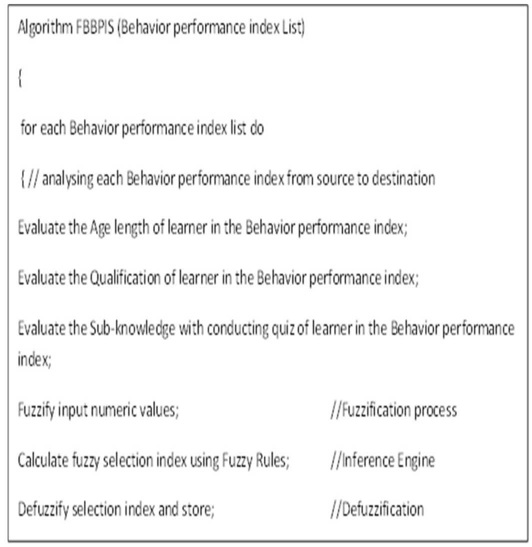
Figure-2 Fuzzy logic model and component of fuzzy controller

Subject knowledge, the third parameter, directly influences the learner's behavioral performance index. Higher subject knowledge corresponded to a higher performance index. Students with low subject knowledge had a low behavioral performance index, those with average subject knowledge showed an average index, and those with good subject knowledge exhibited a high index.

The proposed system employs a fuzzy controller to optimize these parameters. Figure-3 illustrates the Fuzzy Based Course Material Selector (FBCMS) algorithm, designed to determine the behavior performance index. The FBCMS fuzzy controller uses an index list as input and leverages expert knowledge and experience to create a rule base with linguistic if-then rules. Control actions are derived from this rule base by utilizing fuzzy sets and fuzzy inferences as fundamental principles. The process involves fuzzification, rule-based and inference engines, defuzzification, and criteria for selecting the most appropriate learning level for course material.

a) Fuzzification process: The fuzzification process involves converting the numeric values of different input parameters into linguistic values for use in the fuzzification process of the controller. In this design, the fuzzy values utilized were low, average, and high. The fuzzifier determines the values of the input parameters such as age (A), qualification (Q), and sub-knowledge (S).Using fuzzy membership functions, the fuzzifier assigns Low, Average, High fuzzy values to the numerical values of A, Q, and S. The fuzzifier utilizes a trapezoidal membership function, depicted in Figure-4 to Figure-7, to map the numerical values of A, Q, and S to their corresponding fuzzy values. The fuzzy membership function shown in Figure-4 depicts how the numerical values of age group count age are mapped to fuzzy values: low-age, medic-age, and high-age for the age variable.

Low-age: Trapezoid function - [0, 15, 25, 35]
Med-age: Trapezoid function - [28, 35, 45, 50]
High-age: Trapezoid function - [45, 50, 75, 75]



Algorithm FBBPIS (Behavior performance index List)

{

for each Behavior performance index list do

{ // analysing each Behavior performance index from source to destination

Evaluate the Age length of learner in the Behavior performance index;

Evaluate the Qualification of learner in the Behavior performance index;

Evaluate the Sub-knowledge with conducting quiz of learner in the Behavior performance index;

Fuzzify input numeric values; //Fuzzification process

Calculate fuzzy selection index using Fuzzy Rules; //Inference Engine

Defuzzify selection index and store; //Defuzzification

Figure-3 Algorithm of Fuzzy Based Corse Material Selector (FBCMS) controller

In Figure-5, you can see the fuzzy membership function for Qualification which shows how the linguistic values of a learner's qualification index are mapped to fuzzy values such as HSC (Low), UG (Med), and PG & Plus (High).

HSC: Trapezoid function - [0, 0, 25, 40]
UG: Trapezoid function - [30, 40, 55, 70]
PG: Trapezoid function - [60, 70, 100, 100]

In Figure-6, shows the Fuzzy membership function for Sub-knowledge, which help to convert the linguistic values of a learner's subject knowledge into fuzzy values such as Low, Avg, and Good or High.

Low: Trapezoid function - [0, 0, 25, 40]
Average: Trapezoid function - [30, 40, 55, 70]
Good: Trapezoid function - [60, 70, 100, 100]

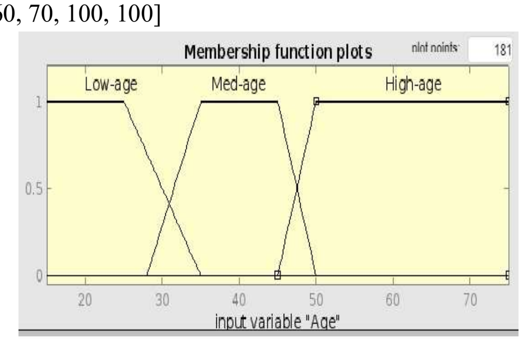


Figure-4 Membership function for Age value

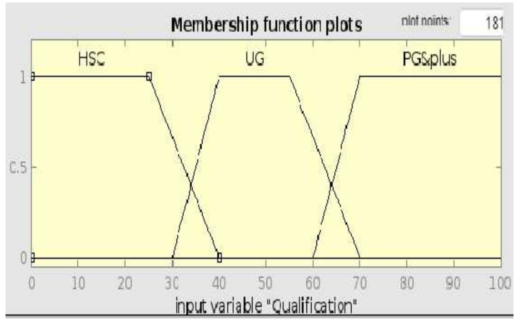


Figure ure-5 Membership function for Qualification

Figure ure-5 Membership function for Qualification

In Figure-7 shows fuzzy output Behavior Performance Index (BI)

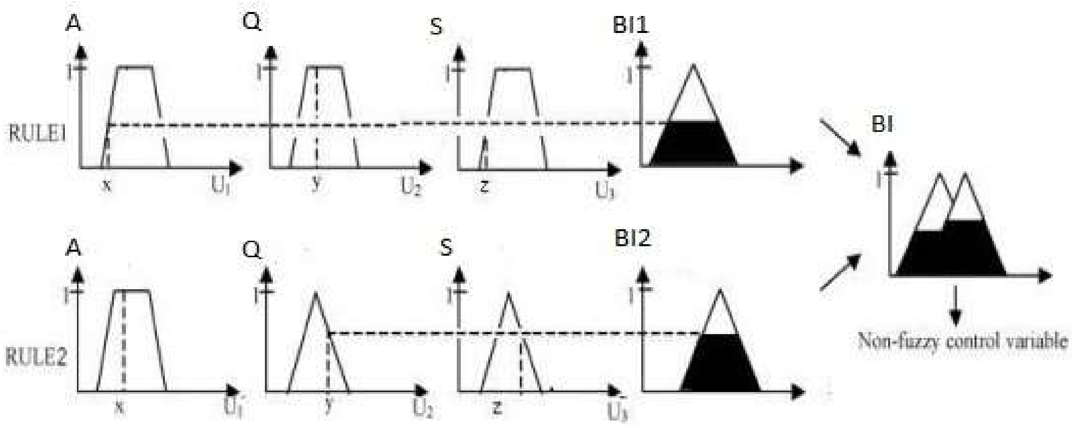


Figure-8 Fuzzy Inference Procedure

Low: Trapezoid function - [0, 0, 25, 40]

Average: Trapezoid function - [30, 40, 55, 70]
Good: Trapezoid function - [60, 70, 100, 100]

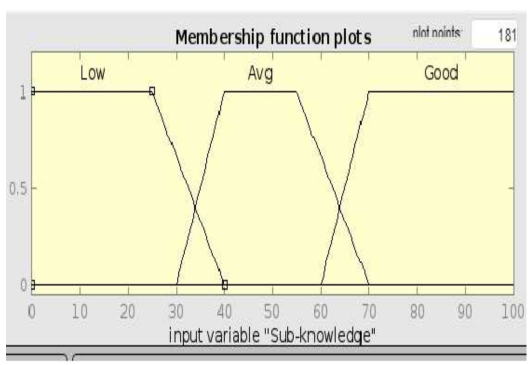


Figure-6 Membership function for Qualification value

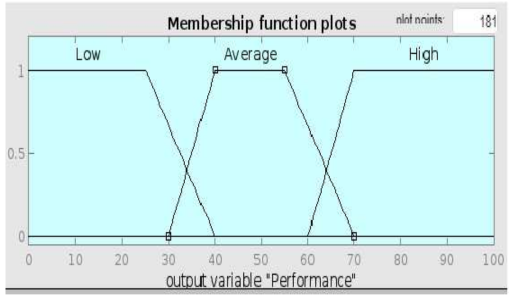


Figure-7 Fuzzy output Behavior Performance Index

The performance of the students was low, and the behavioral performance index value was below 40%. The performance of the student average, behavior performance index value 40% to 70%, and performance of the student high then behavior performance index above 70%.

b) Inference engine and rule base: The production of a fuzzy set by the inference engine results from the application of the rule set to the fuzzification process that involves linguistic values. The outcome of the inference engine is a fuzzy set known as the fuzzy control action. The inference engine takes the fuzzy values of Age, Qualification, and Sub-knowledge from the fuzzifier as inputs and implements the fuzzy control action. The selection index provides information on the level of learning material. Fuzzy rules are expressed as conditional statements in the if-then form. The deduction of the rule is referred to as inference and necessitates the definition of a membership function that characterizes this inference. By using this function, we can establish fuzzy rules based on the inputs to determine the performance index of the behavior as shown in Table1.

c) Defuzzification: The fuzzy controller component is tasked with converting the fuzzy selection index from the inference engine into a crisp value. The performance selection index for each learner's output variable is determined through the implementation of the centroid of area method by [17] for defuzzification. These real values are stored in the performance index list. The Mamdani Fuzzy Inference System was used with the fuzzified input variables Age, Qualification, Sub-knowledge, and fuzzified output variable Performance, and the Rule set

Table1. Fuzzy Rules for Rule Base used in FBCMS Fuzzy Controller

1.	If A is Low-age Λ Q is PG Λ S is Good than BI is High	**15**	If A is Med-age Λ Q is UG Λ S is Low than BI is Average
2	If A is l Low-age Λ Q is PG Λ S is Average than BI is High	**16**	If A is Med-age Λ Q is HSC Λ S is Good than BI is Average
3	If A is Low-age Λ Q is PG Λ S is Low than BI is Average	**17**	If A is Med-age Λ Q is HSC Λ S is Average than BI is Low
4	If A is Low-age Λ Q is UG Λ S is Good than BI is High	**18**	If A is Med-age Λ Q is HSC Λ S is Low than BI is Low
5	If A is Low-age Λ Q is UG Λ S is Average than BI is Average	**19**	If A is High-age Λ Q is PG Λ S is Good than BI is High
6	If A is Low-age Λ Q is UG Λ S is Low than BI is Average	**20**	If A is l High-age Λ Q is PG Λ S is Average than BI is High
7	If A is Low-age Λ Q is HSC Λ S is Good than BI is Average	**21**	If A is High-age Λ Q is PG Λ S is Low than BI is Average
8	If A is Low-age Λ Q is HSC Λ S is Average than BI is Low	**22**	If A is High-age Λ Q is UG Λ S is Good than BI is High
9	If A is Low-age Λ Q is HSC Λ S is Low than BI is Low	**23**	If A is High-age Λ Q is UG Λ S is Average than BI is Average
10	If A is Med-age Λ Q is PG Λ S is Good than BI is High	**24**	If A is High-age Λ Q is UG Λ S is Low than BI is Average
11	If A is Med-age Λ Q is PG Λ S is Average than BI is High	**25**	If A is High-age Λ Q is HSC Λ S is Good than BI is Average
12	If A is Med-age Λ Q is PG Λ S is Low than BI is Average	**26**	If A is High-age Λ Q is HSC Λ S is Average than BI is Low
13	If A is Med-age Λ Q is UG Λ S is Good than BI is High	**27**	If A is High-age Λ Q is HSC Λ S is Low than BI is Low
14	If A is Med-age Λ Q is UG Λ S is Average than BI is High		--- --- ---

A-Age of the learner; Q-Qualification of learner; S-Sub-knowledge; BI-Behavior performance Selection Index

as described above. Mamdani's implication criteria are associated with linguistic values that describe the degree of inference action, as explained by taking an example, as shown in Figure-8. Fuzzy logic inference was applied to determine the behavior performance index.

BI1= If A is Low-age Λ Q is PG Λ S is Good (RULE1)
BI2= If A is Med-age Λ Q is UG Λ S is Average (RULE2)

The "min" function typically serves as the operator, representing the output variable's value domain. The fuzzy control output BI is derived from aggregating all fuzzy subsets BI_i, with their membership values A, Q, and S determined by their disjunction operation described as:
BI = BI1 V BI2 (Aggregation)
Here, the disjunction operator V is the "max" function.

Algorithm Steps:
Initialize: Define linguistic variables and fuzzy sets for each input and output variable.
Input: Take values for Age (A), Qualification (Q), and Subject Knowledge (S).
Fuzzify: Determine the membership grades for each input variable.
Rule Evaluation: Evaluate the fuzzy rules to determine the fuzzy output.
Inference Mechanism: Apply the inference mechanism (Mamdani) to combine the fuzzy outputs.
Defuzzify: Convert the fuzzy output into a crisp value to get the behavior performance index.

d) Behavior performance selection Index Criteria: The selection index for performance indicates the level of course material selection. The algorithm for selecting behavior performance index in the fuzzy controller ultimately establishes the level of course material by utilizing the behavior performance selection index of each learner. The learner with the highest selection index is assigned the advanced course material.

3.3. Content Adaptation Module

After classifying the learner, the system adjusts the course content by:

- Adjusting Complexity: Beginners receive simpler explanations and more foundational exercises, while advanced learners receive complex problems.
- Personalized Feedback: Feedback is tailored according to the learner's progress and knowledge level.
- Dynamic Content Delivery: Depending on the learner's speed, the system can present additional exercises or speed up the delivery of new concepts.

3. Implementation of "AILES"

As discussed in the previous section replacing a similar type of course material for different learners with different knowledge levels with automatic or intelligence-based selection methods that provide course material according to the knowledge level of the learner. Implementation of an adaptive intelligent learning and evaluation system with different components such as registration/login, filling required behavioral parameters, subject knowledge evaluator, fuzzy-based course material selector (FBCMS), and Tutor Module.

3.1 Registration/ Login Module

Implementing a student registration and login system for an adaptive intelligent learning and evaluation system involves ensuring both usability and security.

4.1.1 User Registration

Upon registration, create a user profile that includes fields for learning preferences and past performance data. Collect necessary information: username, password, email, etc. Validate inputs to ensure correctness (e.g., valid email-id format and strong password requirements).Implement email verification to ensure that the email address is valid and belongs to the user. Store the user information securely in the database. Hash passwords using strong hashing algorithms (for example crypts)to protect user credentials. Ensure that the registration processes are user friendly and accessible. Implement a responsive User Interface (UI) that works well across devices (desktop, tablet, and mobile). Include clear navigation menus and easy access to different sections of the system (courses, assessments, exercises, etc.).

Figure-9 Automatic Evaluation of learning parameters and learning material preference

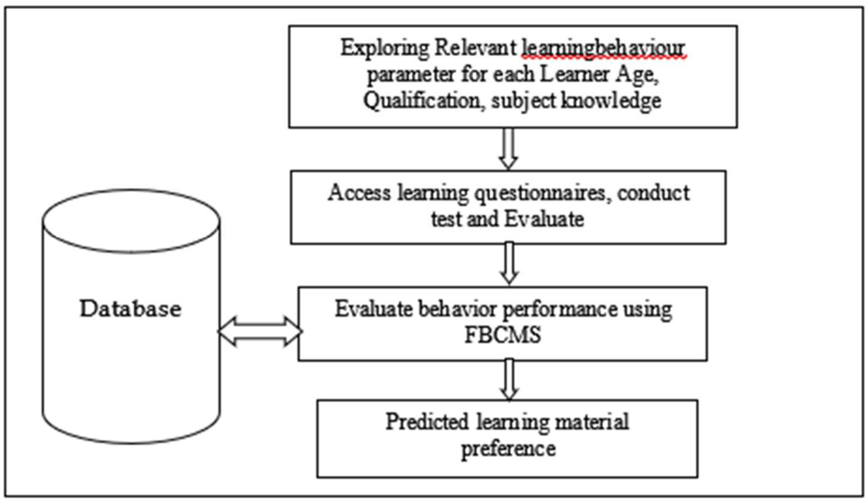
4.1.2 User Login

Requests user credentials through a login interface. Implementation of client-side validation to ensure that basic requirements are met (e.g., fields are not left blank). Authenticate user input against securely stored password hashes. Modify user profiles based on ongoing educational interactions (e.g., course advancement and assessment outcomes). Employ Fuzzy logic algorithms to examine user patterns and customize educational content accordingly. Offer-tailored suggestions for courses, modules, or learning trajectories based on individual user profiles. Develop a system for creating and administering evaluations (such as quizzes and tests). Incorporate various question formats (e.g., multiple choices) to address different learning goals.

These steps will result in a comprehensive and user-centric registration and authentication system for an adaptive, intelligent learning and assessment platform, ensuring that both security and ease of use are prioritized throughout the development process.

3.2 Assessment of the behavior parameters of student

The process of AILES must be adapted so that it can incorporate both types of adaptive learning parameters while modeling the student/learner system. This process system automatically evaluated learning parameters using an FBCMS controller that explored behavioral parameter preferences, age qualification, subject knowledge, for each learner, and the subject knowledge of behavioral parameters conducting quizzes/tests using the 20 alternate objective-type questions each have three marks as shown in Figure-9.



4.2.1 Explore Relevant Behavior each Learner

First, we explored the relevant behavioral parameters for each learner, which consisted of Age, Qualification, subject knowledge, and defined parameter-dimension values. The student model contains factual and behavioral data about an individual learner/student, for example, name, email-id, age, qualification, subject knowledge, background, and preferences of the student/learner, which course to be learned. The learner first enters all these parameters, followed by the FBCMS selector process age, qualification, and subject knowledge.

4.2.2 Subject knowledge Evaluator of the student/learner

The behavioral parameter subject knowledge was evaluated by initially conducting a selected subject test. Initially preparing the 20 objective types of questions and each question carry 3marks and the wrong answer will be negative marking deduct 1 mark in the total score. The system conducted a test and automatically evaluated the test results.

4.2.3 Evaluate the Parameters

The Learners' information was stored in a database. FBCMS fetches that information, then checks and validates these parameters and evaluates the behavior performance according to age, qualification, and subject knowledge. FBCMS then evaluates the learner's behavioral performance index. The behavior performance index level (below average, average, and above average) provides the learning materials(basic, moderate, and advanced) according to the level of the learner(course contents, examples, exercises, and exam). These calculations are based on the fuzzy system FBCMS.

4.2.4 Validation of Fuzzy Controller FBCMS

The FBCMS fuzzy controller of the AILES uses the fuzzy membership values for the input parameters, as given in Table-2.

Table 2 Fuzzy Membership of Input Parameter

Input Parameters → Fuzzy value ↓	Age (A)	Qualification (Q)	Sub-knowledge (S)
Low	≤35	HSC	≤40
Average	>35and ≤50	UG	>40 and ≤70
High	>50and ≤75	PG & above	>70and above

The fuzzy controller 'FBCMS' was validated in MATLAB by choosing different input parameter values from AILES and then calculating the behavior performance index selection using the obtained fuzzy values after applying fuzzy rules. Figure-10 (a) & 10 (b) illustrate the three boundary cases. In case-1, the value of Age (A) = 45 years, Qualification (Q) = 50%, and Sub-knowledge (S) = 50%, compared to the behavior performance index= 49.9%. In case-2, the value of Age (A) = 25 years, Qualification (Q) = 70%, and Sub-knowledge (S) = 55%, compared to the behavior performance index= 82.6%. The inference engine mapped these values onto a rule base and provided behavior performance selection index values of 49.9% and 82.6% on a scale of 3. This validates our FBCMS, as the selection index is high for advanced-level course material, average for moderate level, and low for basic course material as compared to the same level of course material of the learner.

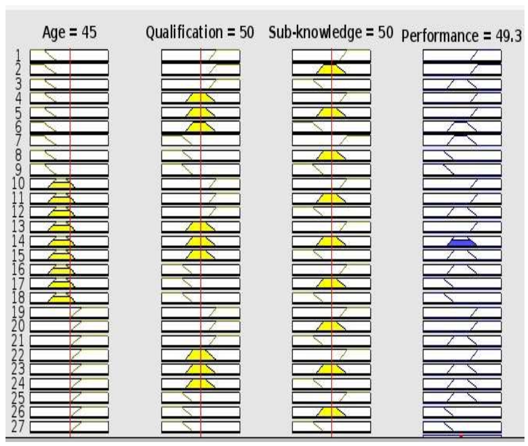


Figure 10(a) Application of aggregation method to determine performance selection index Case-1

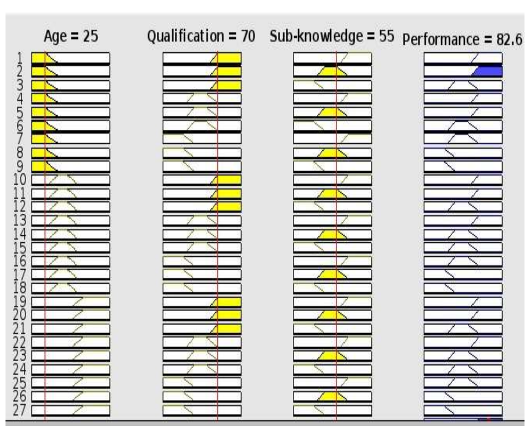


Figure 10(b) Application of aggregation method to determine performance selection index Case-2

The control surface of the FBCMS fuzzy controller represents the nonlinear transformation of inputs to outputs.

This transformation is depicted in a nonlinear surface plot that illustrates the relationship between the input and output of the controller. In the context of the FBCMS with three dimensions, Figure-11 displays the control surface. The undulating surface is a result of the interaction between fuzzy rules and membership functions. The output selection index was determined by considering the combined effects of the activated rules at any given time.

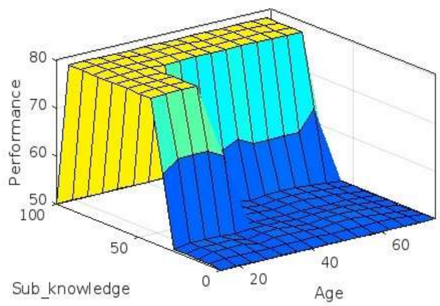


Figure-11 Nonlinear control surface of FBCMS for designed fuzzy rules

The proposed new fuzzy-based controller FBCMS offers significant improvements in optimizing the different levels of learning course material, providing each learning according to the behavior performance index, and making the proposed system not only learn course content efficiently but also improve the learner knowledge level. The proposed system provides more time saving in a large area or word wider than a small area or classroom teaching when compared to the fuzzy-based e-learning system.

3.3 Tutor and Evaluation Module

The tutor and evaluation module are part of an adaptive intelligent learning and evaluation system. This module supports personalized learning and effectively assesses student progress. This module involves a given structured approach to implement the tasks mentioned above:

4.3.1 Tutor Module

The tutor module focuses on delivering personalized learning experiences tailored to each student's needs and pace. This module helps analyze student performance and behavior to recommend appropriate learning course materials and offers adaptive content delivery based on the assessment results, learning preferences, and past performance of the learner. This module provides content recommendations in which serves dynamically generated content (lessons, quizzes, and exercises) based on the student's current proficiency level and learning objectives. Provide feedback loops where students can review their progress and adjust their learning paths accordingly. This module also provides extra interactive elements such as simulations, virtual labs, or multimedia content to actively engage students and integrates live chat features to provide real-time assistance and answer student queries.

4.3.2. Evaluation Module

This is second part of fourth component of AILES. This evaluation module focuses on assessing student learning outcomes and providing feedback to facilitate continuous improvement. This module works in three phases. The first supports various types of assessments (quizzes or tests) to evaluate different aspects of student knowledge and skills. Allow educators to create custom assessments aligned with specific learning objectives and curriculum standards. The second implement automatic grading for objective questions (multiple-choice) to provide instant feedback or grading. Use scoring guidelines for subjective assessments (multiple-choice questions, essays, projects) to ensure consistency and fairness in grading. And third generate analytics and reports on student performance, including scores, progress over time, and areas of strength or weakness. Present data through visualizations (charts, graphs) to help educators and students easily interpret and analyse results.

4.3.3. User Experience

This is third part fourth component which provides user friendly interface and feedback mechanism. The user-friendly interface simplifies navigation between tutoring sessions, assessments, and performance analytics. Ensure accessibility across devices (desktops, tablets, mobile devices) for a consistent user experience. The feedback mechanism incorporates students to provide feedback on their learning experiences, including the effectiveness of tutoring sessions and clarity of assessment criteria.

This component gives a robust and user-friendly interface for an adaptive intelligent learning and evaluation platform, ensuring security, usability, evaluation, and assessment with prioritized throughout fuzzy based course selection method FBCMS.

4. Performance Evaluation of Proposed AILES

The proposed system AILES is combination of student registration/ login, behavior parameter assessment, fuzzy based course material selector (FBCMS) and tutor/ evaluation module. The flow of process of AILES is shown in Figure12. After implementation this system works satisfactory from registration to course completion by the learner.

At the time of registration learner gives initial information (name, email-id, age qualification and subject knowledge). Entered information is stored in database. The design of database is not shown here. The behavior performance index (BI) of the learner using FBCMS, the system automatically provides the grade point and predict which type of subject material are proved to the learner.

In case of learner name is Alisha, email-id, age is 17, qualification 12 standard students and subject knowledge acquiring by conducting test. Her test result is below average then system component FBCMS selects basic type of course material of chosen subject. It proves that the proposed system takes satisfactory decision to provide appropriate course material to Alisha. According to system, Alisha raises good queries during his study of course. The performance of quizzes, assignments and final exam is very good then system promotes automatically in

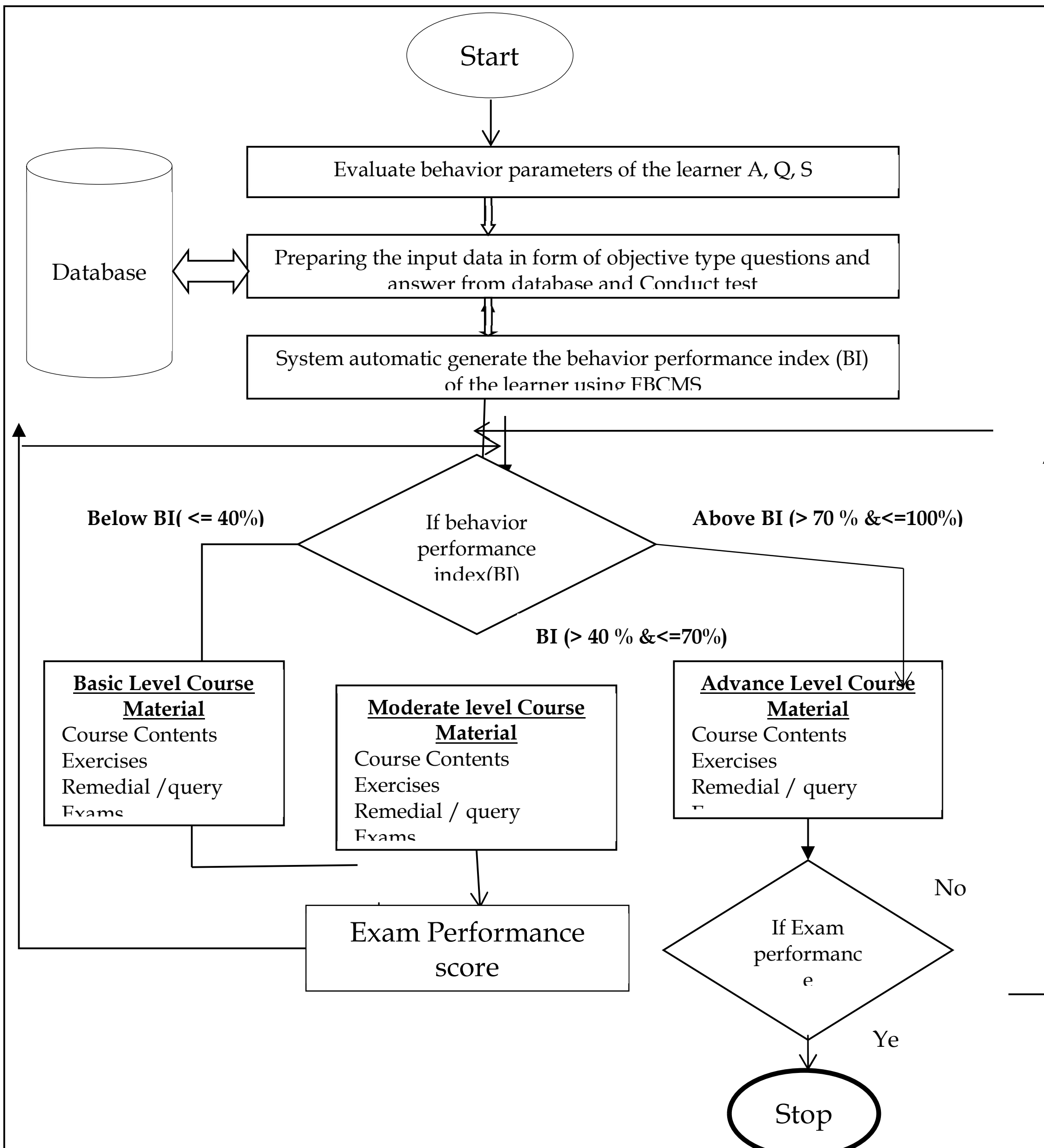


Figure-12 Course material according to student performance next-to-next level mean advance course material. This system helps to learn to Alisha advance course contents and then she is able to solve the exercises. When Alisha appears in final exam of advance course, she achieves satisfactory performance. This result again proves the authenticity of proposed system.

Thus, the successful learning at all the stages will help students to grasp learning material with ease and the content will also prove helpful in enhancing the content, subject matter and facing exam will be helpful in evaluating their knowledge skills as well.

The results indicated that the fuzzy logic-based adaptive learning system outperformed traditional rule-based models in terms of learner satisfaction and learning gain. Learners classified as "Beginners" showed an average improvement of 30% in post-test scores, while "Intermediate" and "Advanced" learners showed improvements of 20% and 15%, respectively. Additionally, the average classification time was reduced by 15% compared to machine learning-based methods, demonstrating the system's efficiency in adapting to learner needs.

5. Conclusion and Future Work

These findings indicate that incorporating fuzzy logic into learner classification improves the adaptability of educational systems. In contrast to conventional approaches, fuzzy logic enables more sophisticated interpretation of learners' traits, accommodating various learning paces and engagement levels. Adaptability is essential for establishing a more efficient learning environment tailored to individual requirements. Moreover, the ease of implementing fuzzy logic models makes them an attractive option for educational institutions aiming to upgrade their adaptive learning systems without relying extensively on intricate machine learning algorithms.

Nevertheless, the process of fully harnessing the potential of this system is ongoing, with several areas for future development. Primarily, there is a need for ongoing investigations into refining adaptive algorithms to ensure that they accurately capture the subtleties of individual learning styles and preferences. Additionally, incorporating emerging technologies, such as deep learning, natural language processing, and data analytics, along with the integration of additional data sources, shows promise for further enhancing the adaptability and intelligence of e-learning frameworks. Furthermore, it is crucial to carefully consider the ethical implications of implementing adaptive, intelligent learning and evaluation systems. Ensuring fairness, transparency, and privacy protection is vital in fostering trust and acceptance among students and educators.

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