AI Tutor: Adaptive e-Learning System Using Expert Fuzzy Controllers

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Abstract: AI Tutor is an e-learning system that adapts content to each student's unique learning style. Achieving this level of adaptability requires specialized methods, and the solution presented here employs concepts of information imprecision and fuzzy expert control. Within an e-learning course titled "Introduction to Machine Learning" in an Artificial Intelligence curriculum, three fuzzy controllers were specifically designed and implemented to adjust learning materials in real-time. This personalized approach highlights the strength of fuzzy controllers in e-learning, allowing the course to effectively respond to a wide range of learning preferences. By addressing the imprecision in how information is processed and understood, these controllers handle the variability and uncertainty inherent in individual learning styles. Ultimately, AI Tutor demonstrates the potential of fuzzy logic to enhance adaptive e-learning, creating a more tailored and effective learning experience for students with diverse needs.

1 INTRODUCTION

The development of personalized e-learning systems is one of the key challenges in modern education. In an era of rapidly changing student needs and diverse learning styles, adaptive technologies that enable the tailoring of educational content to individual user requirements are playing an increasingly important role. Building such systems requires flexible approaches that take into account the complexity of educational processes and the imprecision of data on student behavior. These systems can be developed using different techniques, such as rule-based systems that leverage expert knowledge, or machine learning methods that learn from large data sets (Caro et al., 2015; Fenza et al., 2017). Among these solutions, an encouraging alternative is advanced fuzzy controllers capable of dynamically adapting educational content in response to individual student interactions.

Fuzzy controllers based on expert knowledge provide an alternative to traditional machine learning methods, which typically require large data sets for training. Unlike these methods, fuzzy controllers rely on rules developed from teachers' experience and designed specifically to incorporate imprecise information. The ability to process such information is critical in the educational process because many phenomena that teachers consider are based on numerous factors that are difficult to define precisely, such as student motivation, the pace of material assimilation, or individual learning challenges (Kasinathan et al., 2017; Santos et al., 2020). By using fuzzy modeling, adaptive e-learning systems can effectively account for these complex and subjective aspects when personalizing learning paths.

The aim of this article is to present the concept and application of fuzzy controllers in adaptive e-learning systems. Special emphasis is placed on analyzing their ability to adapt content based on variable and diverse student behavior. A solution is presented in which three different fuzzy controllers were implemented within a single e-learning course to enable adaptation that takes into account student progress and engagement. Depending on the personal learning advancement, the course takes different forms and adapts to the identified needs. An important feature of the proposed solution is the ease of interpretation of its behavior by the teachers, thanks to the transparency of the rules constructed, which makes it easier to adjust the behavior of the

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system whenever the teacher identifies a need for modification.

2 BACKGROUND

Research on adaptive content and adaptive learning systems has been conducted since computers were first introduced in education (Böcker et al., 1990). Beyond educational settings, adaptive content is also valuable in areas such as marketing, e-commerce, and recommendation systems (Casillo et al., 2021; Desai, 2022; Vinaykarthik and Mohana, 2022). The development of adaptive content is critical for personalizing the learning experience, which is essential in modern education.

E-learning courses with adaptive content are defined by their ability to adjust material based on factors like the learner's individual preferences or progress within the course (Dorça et al., 2017; Ennouamani and Mahani, 2017; Premlatha and Geetha, 2015; del Puerto Paule Ruiz et al., 2008).

Several solutions leveraging learning styles for content adaptation in adaptive e-learning courses are found in the literature. For instance, in 2017, Fabiano A. Dorça and colleagues developed a solution recommending additional content based on a pre-defined ontology that links relationships among learning objects to learning styles in the Felder-Silverman model (Dorça et al., 2017). Similarly, in 2019, Nisha S. Raj and Renumol V. G. proposed an adaptation approach grounded in the Felder-Silverman model, delivering course content according to a rule-based system (Raj and V G, 2019). In 2021, Hassan A. El-Sabagh introduced a method for identifying learning styles using the VARK model (Fleming, 2006; El-Sabagh, 2021). His study also demonstrated that adapting content based on learning styles had a statistically significant positive impact on student engagement, measured by Marcia Dixson's 48-item engagement scale, assessing skills, interaction, performance, and emotional engagement (Dixson, 2015).

Adaptation algorithms are not limited to learning styles alone. For instance, in 2017, Giuseppe Fenza, Francesco Orciuoli, and Demetrios Sampson (Fenza et al., 2017) proposed a solution that uses a neural network model trained on data, including inputs from educators. This model generates rules that shape the format of the next task for the student. These rules are derived from the student's actions in previous tasks.

Fuzzy logic, including fuzzy control methods, is also applied in designing e-learning courses with adaptive content (Chandrasekhar and Khare, 2021; Marciniak et al., 2023; Szczepański and Marciniak, 2023). Fuzzy controllers rely on expert knowledge, meaning that the rule base is always developed by specialists in the specific field where the system has some imprecise problems to solve (Zadeh, 1965).

Fuzzy controllers are applied in situations where decisions must be made despite incomplete data or when creating too many rules in a rule-based system is impractical (Mendel, 2017). Their flexibility allows them to manage imprecise or uncertain data, representing it as degrees of membership rather than binary values (Khomeiny et al., 2020). This makes them ideal for adaptive learning systems and other applications, where input data is often unclear or uncertain (Kovacic and Bogdan, 2018). Fuzzy controllers can be used as independent applications or integrated into a more comprehensive adaptive learning system.

The adoption of adaptive content and adaptive learning systems in education has been increasing in recent years. These systems have proven effective in meeting the needs of diverse learners and offering personalized learning experiences (Katsaris and Vidakis, 2021). As digital technologies continue to be widely implemented in education, the demand for adaptive learning systems and content is expected to rise in the future (Sushama et al., 2022). A major advantage of adaptive learning systems is their ability to provide real-time feedback and personalized support, allowing learners to advance at their own pace (Lerís et al., 2017). These systems also offer instructors valuable data on learners' progress, helping them pinpoint areas where extra assistance may be required. This information enables instructors to adjust their teaching methods to better meet the individual needs of learners and enhance the overall learning experience (Gaudioso et al., 2012).

3 AI TUTOR COURSE WITH ADAPTIVE CONTENT

The AI Tutor represents an example of an adaptive e-learning system that dynamically adapts the content of an e-learning course according to a pre-defined adaptation strategy. This strategy has been implemented in the course "Introduction to Machine Learning", which is part of the instructional toolkit used in an Artificial Intelligence curriculum. Designed to introduce the fundamentals of machine learning through practical examples and exercises, this course engaged 89 computer science students enrolled in the course.

3.1 Course Structure

Aligned with the Universal Curricular Taxonomy System (UCTS) (Marciniak, 2014), the “Introduction to Machine Learning” course is structured as a single UCTS Module. This module comprises four UCTS Units, each containing three to eight Learning Objects, including at least one dedicated to review, and is followed by a skills-oriented assessment. At the beginning of the course, students complete a diagnostic test to evaluate their theoretical knowledge of machine learning. At the course’s conclusion, they may take a final skills-oriented test to potentially improve their scores from prior assessments. A screenshot of the initial knowledge-oriented test is shown in Figure 1, while Figure 2 shows an example fragment of the skills-oriented assessment at the end of the “Metrics” UCTS Unit.

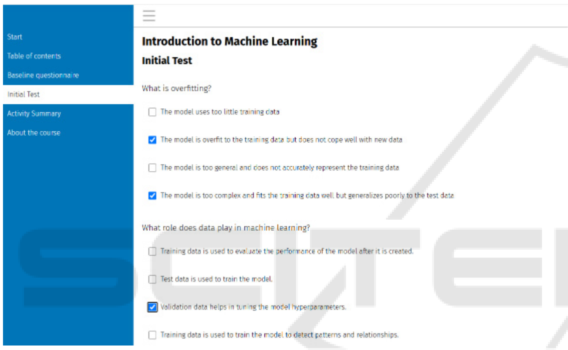

Figure 1: Initial (knowledge-oriented) test in the "Introduction to Machine Learning" course.

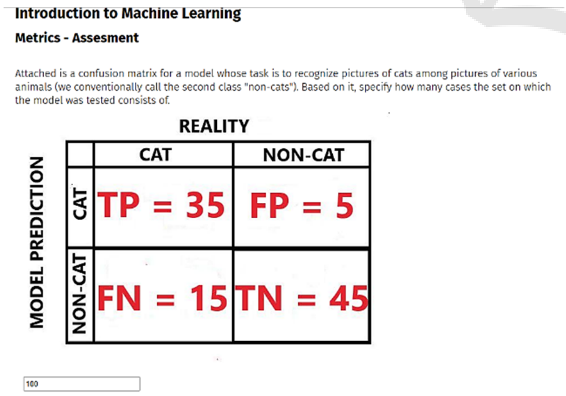

Figure 2: Fragment of the end-of-unit skills-oriented assessment in the "Introduction to Machine Learning" course.

"Introduction to Machine Learning” was developed using the Eduexe e-learning authoring tool (Eduexe, 2024), with references to Google Teachable Machine (Google Teachable Machine, 2019) used to design practical examples and exercises. The course was produced as a package in the SCORM standard with Eduexe platform extensions, allowing the implementation of a fuzzy rule-based system. It was made available to students through Moodle. The course was self-paced and students had six days to complete it. It contained 19 substantive learning objects as well as tests, questionnaires, and technical learning objects that serve an informational function and facilitate navigation through the course. A detailed structure of the course, following the UCTS framework, is shown in Table 1.

Table 1: Structure of “Introduction to Machine Learning” course in UCTS framework.

Course part	No. of Learning objects	UCTS taxon
Introduction to Machine Learning		Module
Initial diagnostic test (knowledge-oriented)		Exam
Introduction	3	Unit
Data in the process of learning	3	Unit
Basic concepts of Machine Learning	5	Unit
Metrics	8	Unit
Final test (skills-oriented)		Exam

An example, an intentionally imperfect Machine Learning model used in the course, prepared using the Google Teachable Machine tool, is shown in Figure 3.

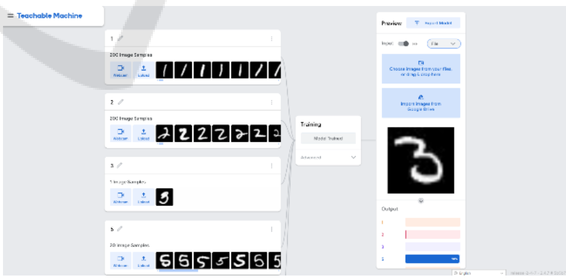

Figure 3: Example Machine Learning model used in the course.

3.2 Content Adaptation Strategy

The AI Tutor system employs a hybrid adaptive strategy, leveraging various content adaptation techniques to achieve three main objectives: (1) maintaining engagement among high-performing students, (2) supporting lower-performing students with additional review materials and exercises, and

(3) minimizing situations where high final scores may not accurately reflect a student's competence level.

The first objective is achieved by continuously measuring each student's Machine Learning Competence indicator, defined as a combination of theoretical knowledge and practical skills. This measurement process includes an initial knowledge-oriented test and skills-oriented assessments at the end of each UCTS Unit. A fuzzy controller synthesizes these results into a Machine Learning Competence score standardized on a scale from zero to one. If a student's score reaches or exceeds 0.8, they are granted unrestricted access to course content, allowing them to complete units in any sequence without needing to complete review tasks or end-of-unit assessments in the order imposed by the course. This adaptation minimizes repetitive tasks for advanced students, aiming to sustain their engagement by preventing boredom.

The adaptive strategy also addresses the needs of students who struggle. If a student with moderate or low Machine Learning Competence fails an end-of-unit assessment, they are directed to supplementary examples and review tasks. Completing these tasks is mandatory before retaking the assessment and progressing in the course.

The third goal of the adaptive strategy seeks to reduce the possibility of a student with low Machine Learning Competence scoring unexpectedly high on the final assessment. Such results could indicate a possible compromise of the test question pool, which may occur in the case of an educational process involving a course that lasts several days and is conducted as self-study without teacher supervision. In a simpler content adaptation strategy implemented in another previously developed course, the use of the disengagement phenomenon was proposed to deliver question pools of the same difficulty level in a controlled manner to users with different levels of learning disengagement (Szczepański and Marciniak, 2023). Disengagement is standardized on a scale from zero to one and is calculated using a fuzzy logic controller that processes inputs related to the quality of student learning (influenced by the frequency of interactions with course elements and the time spent on individual learning objects) and the time remaining before course access concludes (Szczepański and Marciniak, 2023). Low disengagement scores indicate sustained student effort and consistent engagement with the course content, while high disengagement scores suggest a lack of engagement, with students either neglecting course tasks or engaging with them superficially, often when course deadlines approach.

However, it is also possible that a high disengagement indicator is the result of too low a level of course difficulty relative to the high level of user competence – in such a case, this indicator alone should not be the sole premise for the decision to replace the pool of test questions. To ensure a fair and accurate assessment, the AI Tutor system employs a Question Exchange Requirement (QER) indicator, which assigns a value between zero and one based on fuzzy controller outputs from both the Machine Learning Competence and disengagement controllers. If a student's QER indicator exceeds 0.5, the final test questions are selected from an alternative pool of questions of equivalent difficulty but varied content, providing a robust and reliable measure of each student's mastery. Otherwise, questions in the final test are drawn from the pools of questions from the assessments summarizing each UCTS Unit – some questions may be repeated in this way. This is a form of bonus for committed students, helping them improve their final score in the course – however, it is not a discretionary bonus, because it is justified by the Machine Learning Competence developed during the course and by the commitment to perform additional and revision tasks.

4 ADAPTIVE E-LEARNING SYSTEM WITH EXPERT FUZZY CONTROLLERS

The instructional phenomena used in the AI Tutor system's content adaptation framework are characterized by imprecision. To address this, the severity of each phenomenon is categorized into levels defined as low, medium, or high, with these distinctions based on various input parameters. The determination of these severity levels is based on a set of rules defined by domain experts i.e. experienced teachers. These experts construct a structured rule base, which takes the form of *if…then* conditional statements that articulate the relationship between specific input variables and the respective instructional phenomena being modeled.

This rule-based framework serves as the basis for aligning system behavior with expert knowledge. Given the intrinsic ambiguity and variability of the instructional concepts under consideration, as well as the expert-driven nature of the rule base, Mamdani's fuzzy inference model (Mamdani, 1974) was selected as the most appropriate approach to accurately capture and model these instructional phenomena. Mamdani's fuzzy controller facilitates a nuanced representation of imprecise relationships by applying fuzzy logic principles, allowing the AI Tutor system to emulate expert decision-making in content adaptation with a high degree of flexibility and interpretability.

4.1 Machine Learning Competence

According to the content adaptation strategy detailed in Section 3.2, this approach incorporates an evaluation of the student's competence in fundamental machine learning concepts (Machine Learning Competence). This competence level is estimated using Mamdani's expert fuzzy controller, which processes two input variables: (1) the student's baseline knowledge level, represented by their score on an initial diagnostic test (*knowledge*), and (2) their skill level in machine learning fundamentals, reflected in scores obtained from assessments following each course unit (*skill*).

For each input variable, three linguistic values (terms) were defined: low, medium, and high. Minimizing the number of terms and variables simplifies the rule base, making it more accessible and interpretable for the expert – in this case, the teachers. Figure 4 illustrates the membership functions associated with the fuzzy sets representing these linguistic terms.

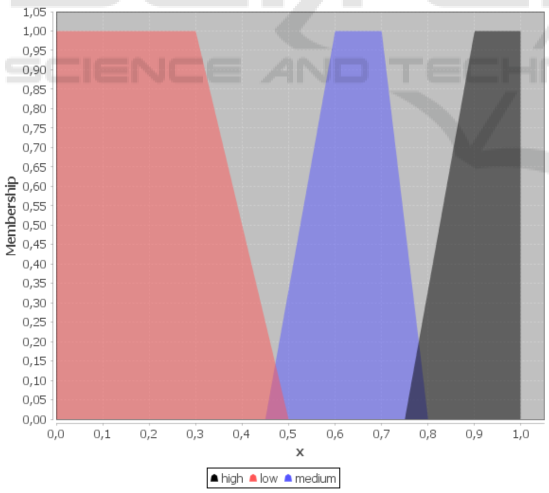

Figure 4: Model of variables values in the controller assessing Machine Learning Competence.

Consistent with the Mamdani fuzzy controller model, an output variable was established within the defuzzification module to represent the student's overall competence level in machine learning fundamentals (*competence*). This output variable was also defined using three terms, mirroring the structure of the input variables (refer to Figure 4).

The definitions of these terms align with the course's grading criteria: a student is deemed to have failed if they score below 50% across course activities, while a score of 75% or above indicates high performance. This alignment ensures that the model's output reflects real-world academic evaluations.

The subsequent step involved developing a rule base, as shown in Table 2, which lists all the fuzzy rules applied in the controller. When constructing the rule base, it was assumed that, within the context of machine learning fundamentals, skills are prioritized over knowledge. For instance, in Rule 3, if the knowledge level is low, but the skill level is high, the overall competence is rated as medium. However, in the reverse situation (Rule 7), where the knowledge level is high, but the skill level is low, the competence remains low.

Table 2: Fuzzy controller rule base for calculating Machine Learning Competence.

No.	Rule
1	knowledge is low and skill is low then competence is low
2	knowledge is low and skill is medium then competence is low
3	knowledge is low and skill is high then competence is medium
4	knowledge is medium and skill is low then competence is low
5	knowledge is medium and skill is medium then competence is medium
6	knowledge is medium and skill is high then competence is high
7	knowledge is high and skill is low then competence is low
8	knowledge is high and skill is medium then competence is medium
9	knowledge is high and skill is high then competence is high

In the rule antecedents, the two input variables are connected by a logical conjunction (*and*), modeled as a minimum operation in the controller, in line with common fuzzy logic practices. The implication (*then*) operator is also defined as a minimum operation.

Through the fuzzy inference process based on this rule base, a composite fuzzy set is generated by summing the individual fuzzy sets produced by each rule for specific input values. The final step in the fuzzy controller's process involves defuzzifying this composite set, with the center of gravity method used to yield a precise output – a widely preferred method for defuzzification in fuzzy systems.

4.2 Disengagement

A further instructional phenomenon incorporated into content adaptation strategies is student disengagement. This phenomenon is also modeled using Mamdani's expert fuzzy controller, which evaluates two input variables: the student's learning quality within the course (*learning_quality*) and the time remaining until the final test, measured from the point at which the student began the course (*remaining_time*). This controller has previously been successfully implemented in another e-learning course which employed a simpler content adaptation strategy (Szczepański and Marciniak, 2023).

The first input variable, the student's learning quality, is defined as an aggregate measure based on three indicators of the student's progress in the course (Szczepański and Marciniak, 2023): the number of interactive exercises completed within the learning materials (*interactions*), the average time spent on each segment of content (learning object) in a given unit (*time*), and the number of content segments (learning objects) in the unit that were not accessed by the student (*not_visited*). The calculation method for learning quality is provided in Equation (1).

$$\text{learning\_quality} = \frac{\text{interactions} + 2 \cdot \text{time} - \text{not\_visited}}{3} \quad (1)$$

A teacher with in-depth knowledge of their students often encounters difficulties in objectively quantifying the factors that influence learning quality. To address this challenge, it is essential to establish a method for the teacher to quantitatively evaluate various aspects of student behavior. The solution proposed here entails creating a formula refined through iterative analysis of student data from prior courses that did not utilize a fuzzy controller. This approach aggregates relevant data, enabling the use of two linguistic variables, which significantly simplifies the rule base construction, requiring only nine rules. Without this data aggregation, the system would need to manage four input variables, potentially expanding the rule base to as many as 81 rules (Szczepański and Marciniak, 2023).

The second input variable for the fuzzy controller, which calculates the phenomenon of disengagement, is the normalized time remaining until the final test deadline, measured from the point at which the student begins engaging with the course. Additionally, the controller defines an output variable – student's disengagement (*disengagement*). Each variable is expressed through three linguistic values: low, medium, and high. The membership functions that map these values to their corresponding fuzzy sets are shown in Figure 5.

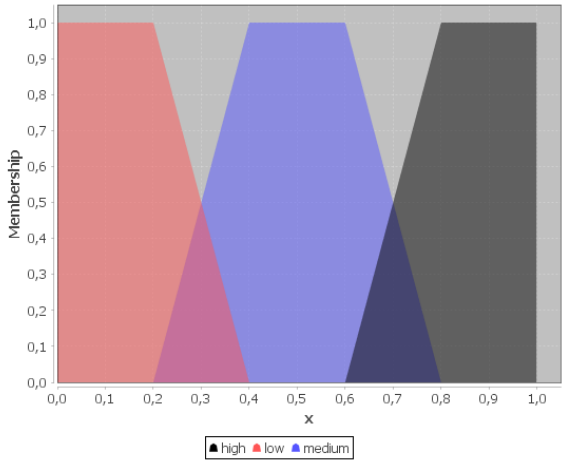

Figure 5: Model of variables values in the controller assessing student's disengagement.

Table 3: Fuzzy controller rule base for calculating student's disengagement (Szczepański and Marciniak, 2023).

No.	Rule
1	if learning_quality is low and remaining_time is low then disengagement is high
2	if learning_quality is low and remaining_time is medium then disengagement is medium
3	if learning_quality is low and remaining_time is high then disengagement is medium
4	if learning_quality is medium and remaining_time is low then disengagement is medium
5	if learning_quality is medium and remaining_time is medium then disengagement is medium
6	if learning_quality is medium and remaining_time is high then disengagement is low
7	if learning_quality is high and remaining_time is low then disengagement is medium
8	if learning_quality is high and remaining_time is medium then disengagement is low
9	if learning_quality is high and remaining_time is high then disengagement is low

The rule base of the fuzzy controller consists of nine rules, as outlined in Table 3. Similar to the fuzzy controller described in Section 4.1, the conjunction operator (*and*) is implemented using the minimum operation, as is the implication operator (*then*). The fuzzy set produced by the controller's inference block is then defuzzified using the center of gravity method.

4.3 Question Exchange Requirement

As outlined in the content adaptation strategy in Section 3.2, the Question Exchange Requirement (QER) indicator plays a key role in determining whether a student should be presented with questions previously covered in the course during the final assessment. This value is computed using Mamdani's expert fuzzy controller, which processes two input variables: the student's competence in fundamental machine learning concepts (*competence* – calculated by the fuzzy controller described in Section 4.1 – Machine Learning Competence controller) and the student's disengagement (*disengagement* – also determined by a fuzzy controller, as discussed in Section 4.2).

In line with the approach used for the fuzzy controller calculating competence in machine learning fundamentals, it was deemed essential to keep the rule base for calculating the QER indicator as minimal and interpretable as possible for the expert. Consequently, the controller is based on two input variables, each defined using three linguistic values: low, medium, and high. These interpretations are consistent across both variables, as shown in Figure 6. Following the Mamdani model, the output variable in the defuzzification block is also defined using three linguistic values, as depicted in Figure 7. The definitions of proposed terms align with the course's grading criteria just as with Machine Learning Competence fuzzy controller.

The next phase in developing the fuzzy controller involved defining the rule base, which is presented in Table 4. This table outlines all the rules employed by the controller. In constructing these rules, it was assumed that the Question Exchange Requirement (QER) is primarily influenced by the student's disengagement. It was recognized that a student's low competence in fundamental machine learning concepts may not necessarily stem from low engagement with the course, and therefore, such a student should not be monitored by the system to the same extent as a student who is actually disengaged or has low activity in the course. For instance, in Rules 1 and 2, the QER indicator is classified as low, accompanied by a low level of disengagement, despite variations in competence levels. A similar pattern is observed in the pairs of Rules 5 and 6, as well as Rules 8 and 9, indicating that disengagement has a more significant impact on the QER indicator than the level of machine learning competence.

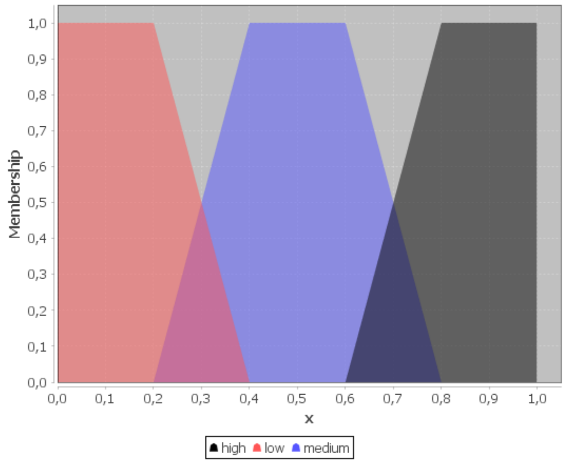

Figure 6: Model of the input variables values in the controller assessing QER indicator.

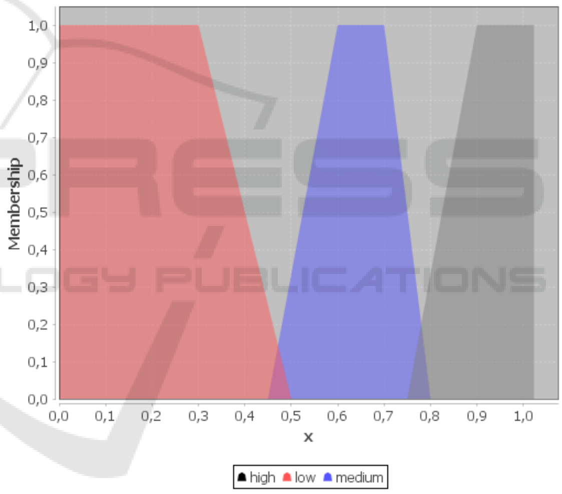

Figure 7: Model of the output variable values in the controller assessing QER indicator.

As with the previously described fuzzy controllers, the antecedents of the rules connect the two input variables through a conjunction (*and*). Both the conjunction and the implication operator (*then*) are implemented using the minimum operation. The fuzzy set resulting from the evaluation of all the rules for specific input values is then defuzzified using the center of gravity method.

Table 4: Fuzzy controller rule base for calculating basic machine learning competence.

No.	Rule
1	if disengagement is low and competence is high then QER is low
2	if disengagement is low and competence is medium then QER is low
3	if disengagement is low and competence is low then QER is medium
4	if disengagement is medium and competence is high then QER is low
5	if disengagement is medium and competence is medium then QER is medium
6	if disengagement is medium and competence is low then QER is medium
7	if disengagement is high and competence is high then QER is medium
8	if disengagement is high and competence is medium then QER is high
9	if disengagement is high and competence is low then QER is high

4.4 Modelling Student Behaviors Using Fuzzy Logic

Fuzzy logic enables the design of inference systems capable of handling discontinuities and non-linearities in decision-making, thereby more closely approximating human-like reasoning more closely than traditional logic systems. This approach results in a significantly streamlined rule base, as demonstrated in the present solution, where each rule base contains only nine rules that are easy to understand for educators. Expecting teachers to create precise rules that capture student behavior using specific numerical thresholds would be highly impractical, as such rigidly defined rules would struggle to accommodate the diversity of student work patterns. Fuzzy logic addresses this challenge by providing a flexible, adaptive framework that simplifies rule configuration and customization, making it more intuitive and effective to model diverse student behaviors.

5 AI TUTOR EVALUATION

The "Introduction to Machine Learning" course described in Section 3 was a part of the Artificial Intelligence class, with 89 students participating. The course was designed to be completed within six days, culminating in a final test. As outlined in the content adaptation strategy in Section 3, once a student's calculated competence level in fundamental machine learning concepts (Machine Learning Competence) reaches a high threshold (at least 0.8), the system grants the student unrestricted access to all course content. Otherwise, sequential access to course components is maintained.

Table 5 presents the representative sample of the collected data about the performance of the fuzzy controller for calculating Machine Learning Competence and illustrates the decision made by the system based on the content adaptation strategy outlined in Section 3.2. The first column of the table represents the initial knowledge level of each student, quantified by the score attained on the initial test. The second column reflects the student's cumulative skill acquisition, represented by the sum of points earned on tests following each course module. The third column displays the student's competence level, as

Table 5: Summary of normalized information about the level of Machine Learning Competence (competence) in fundamental machine learning concepts calculated with the fuzzy controller based on two input variables: (1) the student's score on an initial diagnostic test (knowledge), and (2) their scores obtained from assessments following each course module unit (skill).

Knowledge	Skill	Competence	Decision
0.20	0.95	0.64	Maintaining sequential access
0.80	0.95	0.91	Open access to all course content
0.60	0.65	0.64	Maintaining sequential access
0.80	0.25	0.23	Maintaining sequential access
0.00	0.90	0.64	Maintaining sequential access
0.20	0.25	0.21	Maintaining sequential access
0.40	1.00	0.63	Maintaining sequential access
0.60	0.80	0.89	Open access to all course content
1.00	0.85	0.90	Open access to all course content
0.80	0.45	0.24	Maintaining sequential access
0.40	0.80	0.63	Maintaining sequential access
0.60	0.85	0.90	Open access to all course content

determined by the fuzzy controller. The last column outlines the system's decision regarding the availability of unrestricted access to course content, based on the student's computed competence value. According to the adopted adaptation strategy, full access is granted if the student's competence level reaches or exceeds a threshold of 0.8. The majority of students exhibited insufficient foundational knowledge at the outset of the course, thereby preventing the granting of unrestricted access to all course materials.

According to the content adaptation strategy, when the student is ready to take the final test, the Question Exchange Requirement (QER) indicator is computed. If the QER value is below 0.5, it indicates that the student has demonstrated sufficient engagement throughout the course and possesses a solid level of competence in fundamental machine learning concepts. In this case, the final test consists of questions that were previously included in the course module summary tests (preliminary set of questions). Conversely, if the QER value is 0.5 or higher, it suggests that the student may not have fully engaged with the material, and thus, the final test will feature other questions designed to assess the student's acquired skills throughout the course (alternative set of questions).

Table 6 presents a normalized sample of data about student coursework performance in relation to their level of disengagement which is needed to calculate the QER indicator. The first column represents the system's calculated learning quality, while the second column indicates the remaining time to complete the final test, measured from the moment the student began the course. The third column records the disengagement level as determined by the fuzzy controller. This disengagement value is subsequently used as input for a third fuzzy controller, which computes the Question Exchange Requirement (QER) indicator. Table 7 shows the results of this process, with the first column representing the calculated level of competence in fundamental machine learning concepts, derived from the first fuzzy controller, and the second column indicating the disengagement level. The third column displays the QER value calculated by the fuzzy controller, and the fourth column shows the system's decision regarding the selection of questions for the final test, based on the content adaptation strategy outlined in Section 3.2. When a student's disengagement level reaches at least medium-high, an alternative set of questions is almost certainly selected, unless the student's level of competence in fundamental machine learning concepts is sufficiently high and the student's disengagement level is low or medium.

Table 6: Summary of normalized information about the level of disengagement calculated with the fuzzy controller on the values of Learning Quality and Remaining Time.

Learning Quality	Remaining Time	Disengagement
0.59	0.49	0.50
0.75	0.76	0.26
0.70	0.60	0.38
-0.16	0.01	0.84
-0.04	0.29	0.64
0.09	0.91	0.50
0.53	0.78	0.21
0.60	0.06	0.50
0.82	0.26	0.43
-0.09	0.55	0.50
0.82	0.66	0.17
0.11	0.06	0.84

Table 7: Summary of normalized information the Question Exchange Requirement indicator calculated with the fuzzy controller on the values of Machine Learning Competence (Competence) and Disengagement.

Competence	Disengagement	QER	Set of questions in the final test
0.64	0.50	0.52	Alternative
0.91	0.26	0.22	Preliminary
0.64	0.38	0.52	Alternative
0.23	0.84	0.90	Alternative
0.64	0.64	0.56	Alternative
0.21	0.50	0.64	Alternative
0.63	0.21	0.23	Preliminary
0.89	0.50	0.20	Preliminary
0.90	0.43	0.20	Preliminary
0.24	0.50	0.63	Alternative
0.63	0.17	0.21	Preliminary
0.90	0.84	0.64	Alternative

The fuzzy controllers implemented in the course were designed to reflect the knowledge and experience of the teachers responsible for the classes where the course was introduced. Thus, the results achieved met the expectations of the educators in terms of providing different sets of questions depending on the diagnosed level of student engagement in learning. However, ensuring the effectiveness of these controllers requires an in-depth didactic-psychological study. Such research is essential because student behavior during the course is influenced by various factors, including individual student characteristics, such as their preferred learning style, and different didactic conditions, such as work overload, varying levels of interest in the course topics, or even personal circumstances, such as health challenges. Moreover, such a study is challenging because students engage with the course in an asynchronous mode without direct teacher supervision. Despite these difficulties, this study is planned for the future. It is expected that, given the flexibility afforded by the asynchronous format, a larger proportion of students will complete the course and be evaluated using test questions from the alternative set rather than the preliminary set, allowing for a more comprehensive assessment of the impact of the course.

6 CONCLUSIONS

The development of personalized e-learning systems has become a focal point of modern education. The AI Tutor system, introduced in this paper, is designed to create adaptive content for the e-learning course “Introduction to Machine Learning” providing individualized learning experiences. This system utilizes expert fuzzy controllers, a key technology that is particularly effective in situations where learning data is imprecise or uncertain. By leveraging human-understandable *if…then* rules, the fuzzy controllers help guide students through the course material based on their interaction patterns, allowing for dynamic content adaptation.

Expert fuzzy controllers differ significantly from traditional machine learning methods. They do not require datasets for training, making them an attractive option in environments where data may be sparse or difficult to model. Instead, these controllers rely on expert knowledge, typically drawn from the experience of teachers, to generate the rules that drive the adaptation of learning content. These rules are framed in terms of imprecise concepts reflecting the nuanced nature of learning that is difficult to quantify precisely.

The advantage of expert fuzzy controllers is their ability to handle such imprecision effectively. As a result, they can adapt the course content based on a student's progress and behavior without the need for training cycles. This characteristic makes them well-suited for online education, where individual learning paths can vary significantly. However, this approach does have limitations. One major challenge is that the rule base of the fuzzy controllers may not encompass all possible patterns of student behavior. As a result, there may be scenarios where the controller fails to adapt the content appropriately or misses subtle variations in how students engage with the course material. This limitation highlights the inherent trade-off between the simplicity and flexibility of expert knowledge versus the complexity and adaptability of machine learning-based approaches.

Another potential limitation of the AI Tutor system is the risk that students might attempt to circumvent the system. For instance, students could collaborate on solving tests, leading to discrepancies in how well the system reflects individual learning progress. Although this issue does not undermine the system's ability to personalize content, it points to a need for ongoing analysis of student interactions. In the future, a more in-depth examination of collected data could provide insights into whether such behaviors are widespread and how they impact the overall effectiveness of the system. Addressing this issue will be crucial in refining the system’s capacity to adapt to diverse student behaviors and ensure that it remains an accurate reflection of individual learning experiences.

Looking ahead, there are opportunities to enhance the AI Tutor system by exploring the automatic generation of fuzzy controllers based on collected data. By analyzing student interaction patterns over time, it may be possible to improve the precision of the controllers, either by better modeling the variables used or by identifying additional patterns in student behavior that should be included in the rule base. Alternatively, machine learning models could be trained on the same data and compared with the expert-driven fuzzy controllers. This comparison could shed light on the relative strengths and weaknesses of both approaches, allowing for future improvements to the system.

In conclusion, expert fuzzy controllers provide a promising and effective solution for content adaptation in e-learning environments. By leveraging expert knowledge in a human-understandable form, these controllers can dynamically tailor course content to the individual needs of students. However, the approach does have certain limitations, particularly related to the coverage of all student behavior patterns and the potential for students to circumvent the system. Future work will focus on refining the fuzzy controllers, exploring the integration of machine learning techniques, and addressing behavioral concerns to enhance the system's effectiveness and adaptability.

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