Fuzzy model of knowledge assessment in inclusive education information systems*

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Abstract

The study examines the problem of adaptive knowledge assessment in an inclusive learning environment and proposes a fuzzy evaluation model that takes into account the individual characteristics of learners. The use of fuzzy logic allows for the consideration of uncertainty and incompleteness in input data, making the assessment process more fair and flexible. Based on an analysis of traditional assessment methods, a mathematical model was developed, incorporating parameters such as test results and students' activity during classes. The model was implemented in the MATLAB Simulink environment using a Fuzzy Logic Controller, enabling the automation of the assessment process. The obtained results confirm the effectiveness of the proposed approach and demonstrate its potential for implementation in modern educational management information systems. Future research prospects include expanding the model by incorporating additional parameters, utilizing machine learning methods to optimize fuzzy logic rules, and integrating it with existing educational platforms.

Keywords

Fuzzy logic, knowledge assessment, inclusive education, adaptive systems, Fuzzy Logic Controller, MATLAB Simulink, information systems, learning process modeling.

1. Introduction

Modern educational systems are increasingly oriented toward personalized learning, taking into account various cognitive characteristics and the preparedness level of learners. This trend is particularly significant in an inclusive learning environment, where educational programs need to be adapted to individual student capabilities. One of the promising approaches to addressing this issue is the use of fuzzy logic for knowledge assessment, which enables the development of flexible evaluation models that consider incomplete input data [1,2].

Traditional assessment systems rely on deterministic criteria, often making it difficult to adequately evaluate knowledge in cases where learners do not fit into strictly defined categories. The application of fuzzy logic allows for modeling the assessment process in the form of fuzzy sets and inference rules, contributing to a more accurate determination of knowledge levels [3, 4].

In information systems for inclusive learning environments, implementing fuzzy knowledge assessment models is particularly important. They help eliminate barriers in the learning process, reduce subjective influence from instructors, and enhance the adaptation of educational content to learners' needs [5]. This opens up opportunities for the development of automated decision-support systems in education.

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Thus, the main goal of the study is to develop and validate an adaptive model based on fuzzy logic for assessing knowledge in inclusive educational information systems, aimed at reducing subjectivity, effectively managing uncertain and incomplete data, and improving fairness and adaptability in assessing individual cognitive characteristics of students.

2. Analysis of scientific research

In modern scientific research, significant attention is paid to the implementation of knowledge assessment models in the context of inclusive education. The developed approaches allow for considering the individual characteristics of learners and ensuring a more objective evaluation of their knowledge. For instance, in the dissertation study "Social challenges in modern Ukrainian society in the conditions of martial arts and in the post-war period" an analysis of the sociocultural aspects of inclusive learning is conducted, emphasizing the need for new knowledge assessment methods that account for student diversity [6]. Similarly, in the dissertation by K. Polhun, "Organization of Inclusive Learning in Physics and Mathematics Disciplines for Students with Physical Disabilities in Higher Technical Educational Institutions," the author examines the didactic conditions and models of organizing inclusive education. The study highlights the importance of individualizing the learning process and adapting assessment methods [7], but it does not present specific models or algorithms for developing such an evaluation system.

Scientific studies and publications by American researchers devote considerable attention to the development and implementation of inclusive pedagogical practices. Scholars emphasize the importance of preparing educators for work in inclusive classrooms, stressing the necessity of developing competencies in inclusive education. However, when using information systems as a standard educational tool, the issue of subjectivity arises, and both educators and academic staff face this challenge, particularly in the context of distance learning [8].

In the United Kingdom, where inclusive education is a priority in educational policy, research focuses on developing pedagogical strategies that ensure the full integration of all learners into the educational process. Specifically, there is a strong emphasis on the need to cultivate educators' competencies in inclusive education, which includes understanding and applying various knowledge assessment methods. However, direct methodological examples of knowledge assessment remain limited. Nevertheless, the general approach to individualization in education supports the implementation of flexible assessment models [9, 10].

Research by Lesage highlights the implementation of fuzzy logic for audit risk assessment using imperfect knowledge-based models. This study demonstrates the effectiveness of fuzzy logic for managing uncertainty and incomplete information, particularly relevant in financial and business intelligence systems. It emphasizes that fuzzy models effectively address limitations inherent to traditional deterministic approaches, providing more nuanced decision-support tools capable of handling real-world ambiguity in assessments [11].

Lee and Lin further expanded the application of fuzzy logic in software engineering by introducing a fuzzy risk assessment model defuzzified by the signed distance method. This model enhances software development processes by enabling the consideration of uncertain or subjective factors commonly encountered in software project management. Their approach demonstrated higher reliability and accuracy in identifying and managing potential risks, improving project outcomes compared to conventional assessment methods [12].

Ferraro's study developed a fuzzy knowledge-based model for assessing soil conditions in agricultural systems. By employing fuzzy logic techniques, the research provided an efficient framework for environmental decision-making systems, particularly suitable for complex scenarios involving multiple interacting parameters and uncertainty. This approach significantly improved predictive capabilities in soil assessment compared to traditional linear models, underscoring the versatility of fuzzy systems in diverse information-processing contexts [13].

The work of Liu et al. introduced an RDF data crowdsourcing professional assessment model integrating fuzzy logic principles. Their conceptual approach illustrated the potential of combining fuzzy systems with semantic web technologies, enhancing the quality and reliability of crowd-generated data. This hybridization of fuzzy logic and RDF data demonstrated promising results for knowledge discovery and data verification tasks, applicable across various collaborative information systems [14].

Orłowski and Szczerbicki proposed a conceptual fuzzy model for the mortgage market in Poland, highlighting the use of fuzzy inference systems to improve decision-making and forecasting accuracy. Their study provided evidence that fuzzy logic facilitates better handling of vague economic indicators and market behaviors, suggesting wide applicability of fuzzy methods in economic and financial information systems [15].

In the context of educational information systems unrelated specifically to inclusive education, Pavlova and Kozyra investigated the concept of AI-based information systems aimed at analyzing foreign vocabulary learning. Their results demonstrated the feasibility of integrating artificial intelligence techniques, including fuzzy logic, into language learning platforms to achieve personalized user experiences and improved educational outcomes through intelligent content adaptation [16].

Hovorushchenko and Alekseiko explored predictive modeling techniques, specifically focusing on land surface temperature forecasting within urban sustainability frameworks. By employing advanced modeling and forecasting methods integrated into geographic information systems (GIS), their research demonstrated improved prediction accuracy and robust decision support for urban planners and sustainability experts [17]. Although their work did not explicitly utilize fuzzy logic, the methodologies emphasized reflect broader trends in adaptive predictive modeling applicable to various information management contexts.

From a more general perspective of adaptive information systems, Senkivskyy et al. studied factors influencing the design processes of reference and encyclopedic book editions through advanced computational intelligence methods. Their results demonstrated the practical benefits of computational intelligence algorithms, including fuzzy logic and decision-making systems, which significantly enhanced the precision, efficiency, and adaptability of information publishing processes [18].

Thus, analyzing contemporary research in the broader field of information systems reveals a strong trend toward the application of fuzzy logic, adaptive modeling, machine learning integration, and intelligent decision-support technologies. These approaches offer significant advantages over traditional deterministic methods, primarily through their ability to effectively manage uncertainty, improve decision-making accuracy, and enhance adaptability in dynamic environments. The reviewed studies collectively affirm the relevance and potential of employing fuzzy logic and computational intelligence techniques across diverse information systems beyond inclusive education alone. This establishes a firm theoretical and practical foundation for further development and integration of such models in various application domains, including educational technologies [8, 9, 10].

Thus, an analysis of existing research reveals a common trend toward the integration of inclusive practices and adaptive knowledge assessment methods. Although the direct application of fuzzy logic or other advanced algorithms and methods in knowledge evaluation is not yet widespread, the overarching movement toward individualization and flexibility in education creates prerequisites for the further development [11] and implementation of such approaches in inclusive education systems. Considering the discussed aspects, research on a fuzzy knowledge assessment model in the context of inclusive learning information systems is both relevant and necessary.

3. Material and methods

The study analyzes theoretical approaches such as Lotfi Zadeh's fuzzy set theory (Zadeh, 1965) as a foundation for modeling uncertainty in knowledge assessment. It examines pedagogical concepts of inclusive education, particularly the Universal Design for Learning (UDL) model, which emphasizes the personalization of the educational process. The study also considers expert evaluation methods based on fuzzy numbers, allowing for a reduction in assessment subjectivity [12].

Empirical data were collected, including student test results using both traditional and adaptive assessment approaches. An expert evaluation was conducted with specialists in educational technologies within the field of inclusive learning. Additionally, a thorough analysis of software tools used for assessment was carried out [13, 14].

In traditional student knowledge assessment, which typically involves testing, oral and written exams, and coursework, the level of material comprehension is not always accurately reflected. These methods often fail to account for subjective factors, incomplete information, or ambiguous evaluations. Applying fuzzy logic enables the creation of a model that better accounts for these aspects and provides a more flexible knowledge assessment framework [15,16].

To achieve this, key parameters influencing knowledge assessment were identified, including [16,17]:

- Answer accuracy (excellent, average, low).
- Depth of understanding (complete, partial, absent).
- Logical consistency of explanation (clear, with errors, absent).
- Task completion time (fast, on time, delayed).
- Independence of execution (independent, with assistance, copied).

The next step involved defining fuzzy sets for each parameter [15, 17]:

- Answer accuracy: excellent (0–40%), average (30–70%), low (60–100%).
- Depth of understanding: complete (0–40%), partial (30–70%), absent (60–100%).
- Logical consistency: clear (0–30%), with errors (20–70%), absent (60–100%).
- Task completion time: fast (0–30%), on time (20–70%), delayed (60–100%).
- Independence of execution: independent (0–30%), with assistance (20–70%), copied (60–100%).

Each factor is represented as a fuzzy set with corresponding membership functions.

The Mamdani method was chosen for model implementation, as it is suitable for interpreting results using linguistic variables. Based on this approach, the following rules were established [18,19]:

If (Depth of understanding – high) and (Logical consistency – complete), then Grade – high.
If (Depth of understanding – medium) and (Logical consistency – partial), then Grade – medium.
If (Depth of understanding – low) or (Logical consistency – absent), then Grade – low.

Since the output values are fuzzy, they must be converted into specific numerical values (grades). For this purpose, the Centroid method was selected, as it allows for the calculation of the average value within the fuzzy set, ensuring a balanced and interpretable assessment [20].

4. Fuzzy model of assessing knowledge of education seekers in an inclusive environment

The development of a mathematical model for knowledge assessment in an inclusive learning environment is based on the application of fuzzy logic. Let us denote the set of input parameters considered in the evaluation of learners' knowledge[21, 22]:

$$X = \{x_1, x_2, \dots x_n\}, \tag{1}$$

where:
x_1 – test results (score);
x_2 – level of activity in classes;
x_3 – quality of homework completion;
x_4 – level of independent work;
x_5 – speed of mastering new material;
x_6 – adaptability to new tasks;
x_7 – teacher's assessment of the overall level of knowledge.

Each variable will be represented as a fuzzy set:

$$A_i = \left\{ \left(x, \mu_{A_i}(x)\right) \,\middle|\, x \in X \right\}, \tag{2}$$

where μAi(x) the membership function that reflects the degree of knowledge belonging to the corresponding class (low, medium, high).
For each variable, we use triangular or trapezoidal membership functions [23]:

$$\mu_{A_i}(x) = \begin{cases} 0, x \le a \\ \frac{x-a}{b-a}, a < x \le b \\ \frac{c-x}{c-b}, b < x \le c \\ 0, x > c \end{cases}, \tag{3}$$

where:
a,b,c– parameters that define the boundaries of the category.

The membership functions determine the knowledge level of the learner [23]:

- Low knowledge level: μL(x)
- Medium knowledge level: μM(x)
- High knowledge level: μH(x)

Knowledge assessment is performed using an IF-THEN rule-based system (as in the Mamdani system).
Example of a fuzzy rule [24]:

$$\text{IF } (\text{x}_1 \text{ is High}) \text{ AND } (\text{x}_2 \text{ is Medium}) \text{ THEN y is High}, \tag{4}$$

where the output variable y – represents the final knowledge level.

4.1. Formalization of fuzzy rules

Let there be a set of rules:

$$R_j: IF\ x1\ is\ A_{1j}\ AND\ x2\ is\ A_{2j} \dots\ THEN\ y\ is\ B_j, \tag{5}$$

where:

- A_{ij}– fuzzy sets that define the levels of input variables.

- B_j – fuzzy knowledge assessment.

The aggregation of rules is performed using the Minkowski operator:

$$\alpha_j = \min(\mu A_{1j}(x_1), \mu A_{2j}(x_2), \dots, \mu A_{nj}(x_n)), \tag{6}$$

where α_j is the activation level of the j-th rule.

To obtain the final knowledge assessment, we use the centroid method:

$$y^* = \frac{\sum_{j=1}^{m} \alpha_j \cdot c_j}{\sum_{j=1}^{m} \alpha_j}, \tag{7}$$

where:
c_j – centers of fuzzy sets of output estimates.
m – number of active rules.

4.2. Model validation and calibration

After constructing the model, it undergoes testing and comparison with traditional assessment methods: Empirical testing – using data from students of different groups. Correlation analysis – comparing the fuzzy model's assessments with actual academic performance results. Model stability analysis – evaluating changes depending on the parameters of fuzzy sets [22, 23].
The proposed mathematical model of fuzzy knowledge assessment allows [24]:

- Considering uncertainty and adaptively evaluating learners.
- Using logical rules for automated assessment.
- Minimizing subjectivity in the evaluation process.
- Improving the accuracy and fairness of assessment in an inclusive environment.

4.3. Experiment, results and discussion

Two input variables were defined: TestScore (test score) and ClassActivity (class activity), along with the output variable FinalGrade (final grade).
For each variable, three fuzzy sets were assigned: Low, Medium, High. Triangular and trapezoidal membership functions are used.
Nine IF-THEN rules are applied for knowledge assessment.

Rule 1: IF TestScore is Low AND ClassActivity is Low THEN FinalGrade is Low
Rule 2: IF TestScore is Low AND ClassActivity is Medium THEN FinalGrade is Low
Rule 3: IF TestScore is Low AND ClassActivity is High THEN FinalGrade is Medium
Rule 4: IF TestScore is Medium AND ClassActivity is Low THEN FinalGrade is Low
Rule 5: IF TestScore is Medium AND ClassActivity is Medium THEN FinalGrade is Medium
Rule 6: IF TestScore is Medium AND ClassActivity is High THEN FinalGrade is High
Rule 7: IF TestScore is High AND ClassActivity is Low THEN FinalGrade is Medium
Rule 8: IF TestScore is High AND ClassActivity is Medium THEN FinalGrade is High
Rule 9: IF TestScore is High AND ClassActivity is High THEN FinalGrade is High

The membership functions and the graphical decision surface illustrate how the knowledge assessment changes depending on test scores and student activity.
A teacher or an automated system can use this model for adaptive student evaluation in an inclusive environment.
A schematic model was built using the Fuzzy Logic Toolbox in MATLAB Simulink (Figure 1).

Input variables:

- TestScore (Test Result)
- ClassActivity (Class Activity)

Output variable:

- FinalGrade (Final Grade)

Arrows between variables indicate how input variables influence the output through fuzzy rules [23].

This schematic model illustrates the logical relationships between input and output variables and demonstrates that decisions are made based on fuzzy rules.

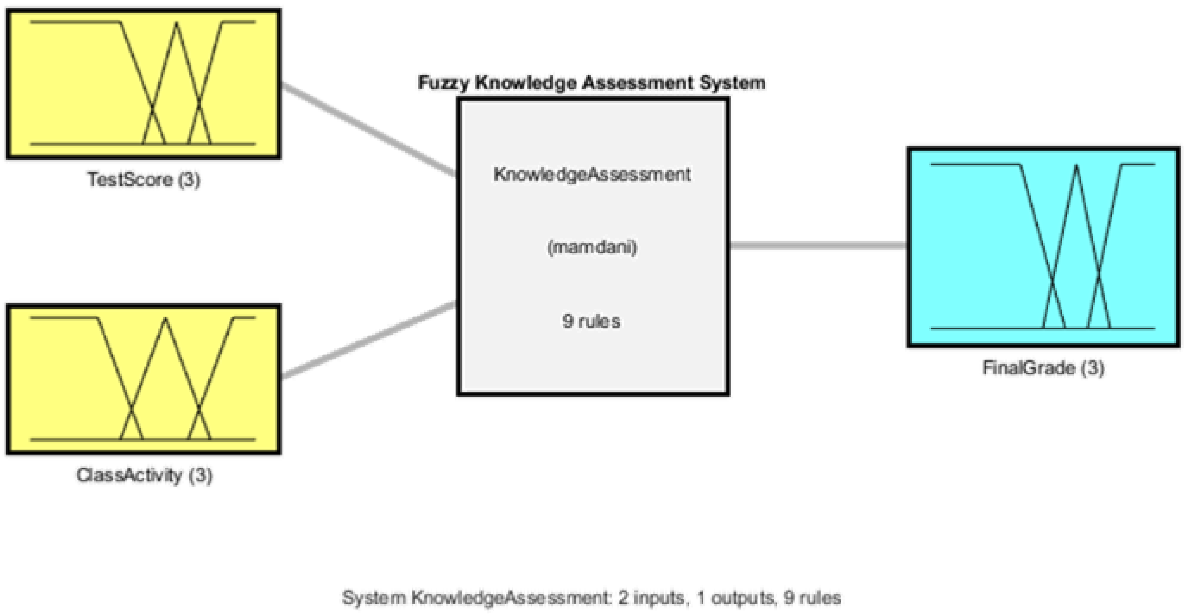

Figure 1: Fuzzy evaluation model model.

After executing the MATLAB code, the following graphs of membership functions were obtained (Figure 2).

Each of the three subplots in this graph corresponds to a specific variable:

- (a) Membership function graph for TestScore – Three fuzzy sets: Low, Medium, High. They are positioned along the X-axis, which represents test scores (0-100). For example, a score of 50 can simultaneously partially belong to both the Medium and Low sets. This means that test results do not have strict boundaries—the same score can partially belong to two categories.
- (b) Membership function graph for ClassActivity – Three fuzzy sets: Low, Medium, High. The values range from 0 to 10. This variable determines how active a student is in class. If a student has an activity level of 4, they may partially belong to both the Low and Medium sets.
- (c) Membership function graph for FinalGrade – Three fuzzy sets: Low, Medium, High. They are positioned along the X-axis within the 0-100 range.

The knowledge assessment result is also fuzzy, meaning students do not receive a fixed grade but instead fall into a certain level depending on various factors.

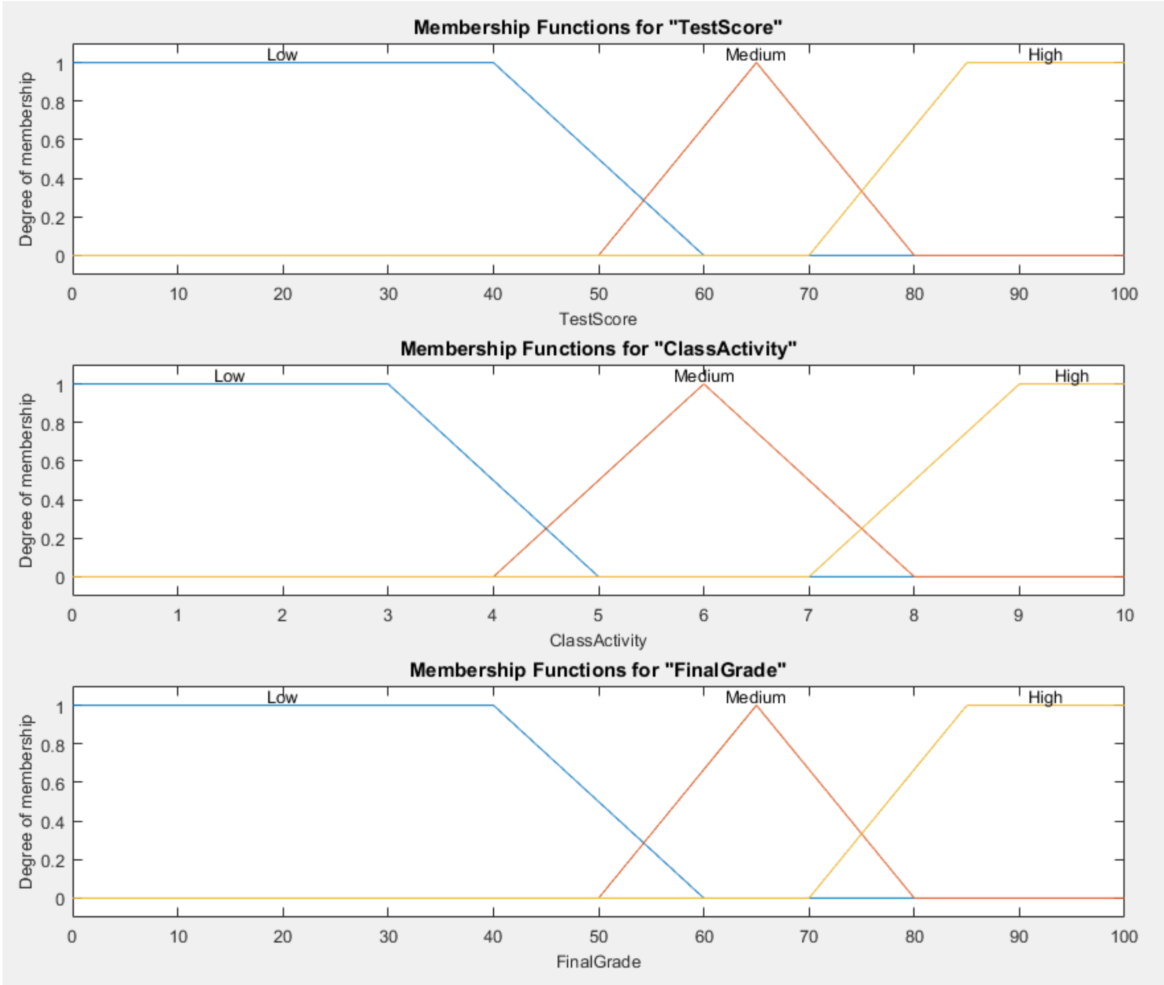

Figure 2: Graphs of membership functions.

The obtained research results confirm the effectiveness of the proposed fuzzy knowledge assessment model in an inclusive learning environment. The implementation of the model in MATLAB Simulink enabled a series of tests, demonstrating the flexibility and adaptability of the method in evaluating students' knowledge. A comparison between results obtained through fuzzy logic and traditional assessment methods revealed several key advantages.

Comparison with Traditional Assessment Methods

Traditional assessment methods, such as grading scales (e.g., 100-point or 5-point scales) or fixed-answer tests, have rigid boundaries and do not account for individual learning differences. For example, if a student scores 59 points on a 100-point scale, they receive a "satisfactory" grade [26, 27], even though their knowledge level might be closer to "good." Additionally, traditional methods fail to consider factors such as class activity, learning speed, or independent work, all of which significantly affect a student's actual knowledge [28, 29].

In contrast, the proposed fuzzy knowledge assessment model enables smooth transitions between grade levels, eliminating the issue of sharp categorization. For example, if a student scores 59–61 points, they may receive a blended grade, partially belonging to both "satisfactory" and "good" categories, accurately reflecting their real knowledge level.

The Simulink model, built on fuzzy logic, utilizes two primary input variables [27]:

- TestScore (test results).
- ClassActivity (class participation).

The output variable – FinalGrade (final score) – is determined using fuzzy rules, allowing for the consideration of multiple factors in the final assessment.

During test simulations with various input data, it was observed that the fuzzy evaluation system adjusts results based on students' activity levels. For instance, two students with the same test score (70 points) but different class activity levels receive different final grades:

- A passive student receives a lower final grade.
- An active student receives a higher final grade.

This is a significant advantage over traditional assessment methods, which would assign the same grade to both students, ignoring their participation in the learning process [27].

The decision surface graph generated in MATLAB Simulink demonstrates gradual changes in final grades depending on test results and activity levels. This confirms that fuzzy logic can better account for uncertainty in the learning process. For example, when test scores range between 60 and 80 points, the system does not make abrupt grade transitions but instead adjusts gradually, aligning with students' actual knowledge levels [28, 30].

The comparative analysis of results demonstrated that the use of fuzzy logic in knowledge assessment produces fairer results compared to traditional methods. The key advantages include:

- Adaptability to students' individual characteristics.
- Elimination of rigid category divisions.
- Consideration of additional parameters (e.g., class activity).
- Automation of the assessment process.

The results confirm the feasibility of fuzzy systems in modern educational information systems, providing a foundation for further improvements in adaptive knowledge assessment methods.

5. Conclusions

The conducted research confirmed the effectiveness of applying fuzzy logic models for adaptive knowledge assessment within inclusive education information systems. The study addressed a relevant scientific and practical task: developing a flexible and objective assessment method capable of adapting to learners' individual cognitive characteristics and needs. Specifically, it aimed to reduce subjective influences, effectively handle incomplete or uncertain data, and ensure equitable evaluation for all students, particularly within inclusive learning contexts.

The analysis of existing scientific research revealed significant gaps in traditional knowledge assessment systems, including rigid categorization, limited adaptability, and insufficient consideration of factors such as student engagement and individual differences in learning processes. By implementing fuzzy logic principles, the proposed approach successfully mitigated these limitations, providing educators and institutions with a robust decision-support tool for fairer and more accurate assessments.

A detailed mathematical model was developed based on fuzzy set theory and fuzzy inference systems, taking into account essential parameters such as test results, students' classroom activity, quality of homework, speed of mastering new material, and independence in performing tasks. By formalizing these parameters into fuzzy sets and implementing a Mamdani inference approach, the model facilitated smooth transitions between knowledge levels, thereby accurately reflecting the nuances of students’ knowledge and skills.

The model was implemented using MATLAB Simulink and validated through comprehensive empirical testing, demonstrating considerable advantages over traditional grading methods. The fuzzy logic-based model effectively addressed ambiguity in knowledge assessment scenarios, enabling educators to perform evaluations that accurately capture learners' real abilities. For instance, students with similar test results but varying classroom engagement received appropriately differentiated assessments, underscoring the model's adaptability and precision.

Comparative analysis between traditional assessment methods and the fuzzy logic approach revealed clear benefits of the latter, including improved flexibility, reduced categorization errors, and enhanced responsiveness to individual learner profiles. This approach also demonstrated significant practical applicability, particularly in inclusive educational settings, where conventional assessment methodologies frequently fall short in accurately measuring learning outcomes.

Furthermore, this research identified several promising directions for future studies. Opportunities exist for model expansion by incorporating additional parameters, such as individual learning pace, adaptability to diverse educational tasks, and quality indicators of independent and collaborative work. Moreover, integrating machine learning algorithms to optimize membership functions and automatically refine fuzzy inference rules holds significant potential for enhancing model accuracy and responsiveness. Such advancements would further strengthen the model's effectiveness, making it suitable for integration into existing educational platforms and Learning Management Systems (LMS).

Thus, the obtained results substantiate the feasibility and effectiveness of applying fuzzy logic models in inclusive education environments. This study contributes both theoretically and practically to the domain, providing educational institutions and educators with advanced assessment methods that better align with contemporary educational standards, fostering fairness, objectivity, and inclusivity in knowledge evaluation practices.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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