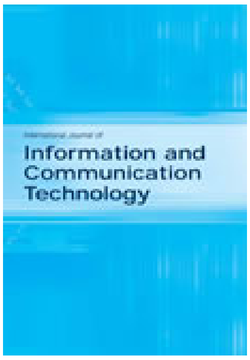

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Adaptive assessment in English language teaching: implementing fuzzy logic for intelligent evaluation

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Abstract: This study explores the integration of fuzzy logic in an adaptive assessment system for English language teaching (ELT), aimed at providing personalised and dynamic evaluations of students' language proficiency. The system evaluates various linguistic components such as grammar, vocabulary, fluency, and pronunciation, by converting these inputs into fuzzy sets and applying a fuzzy inference system to assess overall proficiency. The study evaluates the system through pilot testing, accuracy comparison with traditional evaluation methods, and usability testing. The results demonstrate a high correlation (r = 0.92) between the fuzzy logic-based scores and traditional human evaluations, as well as strong test-retest reliability (r = 0.93), supporting the system's validity and consistency. This study contributes to the field of adaptive language assessment by demonstrating the potential of fuzzy logic in providing personalised, reliable, and efficient evaluation systems in ELT.

Keywords: fuzzy logic; adaptive assessment; English language teaching; ELT; personalised learning; language proficiency evaluation.

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1 Introduction

In recent years, the landscape of education has undergone a significant transformation, driven by the advent of new technologies and methodologies aimed at enhancing the teaching and learning process (Miller, 2023). Among these, English language teaching (ELT) has particularly benefited from innovations that aim to address the diverse needs of learners, improve teaching efficacy, and provide more personalised educational experiences (Sharma, 2023). As the world becomes more interconnected, the ability to communicate effectively in English has become increasingly important (Zilola and Oyshirin, 2023). This underscores the need for effective assessment methods in ELT that not only gauge students' language proficiency but also cater to individual learning styles and needs (AlShareef, 2024).

Traditional assessment methods in ELT, such as standardised tests and exams, have long been the primary means of evaluating students' language skills (Fadilah et al., 2023). However, these methods often fail to capture the full range of a learner's abilities and may not provide an accurate representation of their actual proficiency (Shahriar et al., 2024). These assessments tend to treat all students the same, applying a one-size-fits-all approach that fails to account for individual differences in learning speeds, cognitive processes, and language acquisition challenges (Abdellatif et al., 2024). Furthermore, traditional assessments often struggle to assess more subtle aspects of language use, such as fluency, pronunciation, or contextual understanding (Manggiasih et al., 2023). Given these limitations, there is an increasing demand for more dynamic, flexible, and personalised forms of evaluation that can better serve the diverse needs of English language learners (ELLs) (Anis, 2023).

Adaptive learning technologies have evolved significantly over the past few decades, originating from early computer-assisted instruction in the 1970s. With advancements in artificial intelligence and data-driven analytics, modern adaptive systems can personalise learning experiences based on real-time student performance. The integration of fuzzy logic further enhances these systems by allowing nuanced assessments that account for varying levels of learner proficiency. Adaptive assessment, a method that adjusts the difficulty of questions based on a learner's performance in real-time, offers a promising solution to this challenge (Sajja et al., 2024). Unlike traditional assessments, adaptive assessments are designed to modify themselves in response to a student's abilities, providing a more accurate and tailored measure of their skills. This personalised approach not only offers a deeper understanding of a student's strengths and weaknesses but also promotes a more engaging and supportive learning environment (Almusaed et al., 2023). Adaptive systems have the potential to assess a learner's performance more efficiently, providing real-time feedback and adjusting the assessment process to better match the individual's progress (Mejeh et al., 2024).

Fuzzy logic is preferred over traditional adaptive assessment methodologies due to its ability to handle uncertainty and imprecise data, providing a more flexible evaluation of learner performance. Unlike rigid rule-based systems, fuzzy logic allows for gradual transitions between proficiency levels, ensuring a more personalised and accurate assessment experience. One of the most advanced computational techniques that can be utilised in adaptive assessment is fuzzy logic. Fuzzy logic is a mathematical framework designed to deal with uncertainty and imprecision, which makes it particularly suitable for domains such as language learning, where responses and judgements are often not black and white (D'Aniello, 2023). Unlike classical binary logic, which treats statements as either true or false, fuzzy logic allows for varying degrees of truth. This capability is particularly useful in educational settings, where performance does not always fit neatly into rigid categories (Mendel, 2024). In language assessment, for instance, a student's fluency might be described as somewhat fast, somewhat slow, or moderate, rather than simply correct or incorrect.

Fuzzy logic's potential for transforming adaptive assessment in ELT lies in its ability to model the nuanced, often subjective nature of language learning (Jiao, 2024). It allows for a more flexible approach to evaluation, taking into account the vagueness inherent in language use. For example, when evaluating speaking skills, fuzzy logic can accommodate the fact that a learner's pronunciation may not be perfect, but still understand that they are proficient in certain aspects, such as intonation or rhythm (Mousse et al., 2023). By incorporating fuzzy logic into adaptive assessment systems, educators can create more intelligent, responsive, and individualised evaluation tools that better align with the complexities of language learning.

The primary goal of this article is to explore the application of fuzzy logic in adaptive assessment systems for ELT. It will examine the theoretical framework surrounding adaptive assessment, how fuzzy logic can be implemented to create intelligent evaluation systems, and the potential benefits of such systems for both students and educators. In doing so, the article aims to bridge the gap between cutting-edge technology and language education, presenting a new paradigm for assessing language proficiency that is more in tune with the needs of modern learners. The article will begin by providing an overview of adaptive assessment in the context of ELT, discussing the limitations of traditional assessment methods and the growing demand for personalised evaluation tools. Following this, it will introduce the concept of fuzzy logic, explaining its principles and how it can be integrated into adaptive assessment systems. The discussion will then focus on the practical aspects of implementing fuzzy logic for intelligent evaluation in ELT, including the design of fuzzy inference systems, the creation of membership functions for language assessment criteria, and the adaptation of the assessment process to individual learners. The benefits of using fuzzy logic in adaptive assessment will be highlighted, along with potential challenges and considerations for educators and institutions.

Furthermore, the article will explore real-world applications and case studies where fuzzy logic has been successfully implemented in educational technologies. It will also address the implications of using such systems in ELT, considering their potential to revolutionise language assessment by providing a more personalised, accurate, and efficient method for evaluating learners' language skills. Finally, the article will conclude by offering recommendations for further research and development in this area, highlighting the importance of continuing to innovate and integrate emerging technologies to enhance English language education worldwide.

The integration of fuzzy logic into adaptive assessment represents a promising frontier in the evolution of ELT and learning. By providing a more nuanced, individualised approach to evaluation, fuzzy logic-based systems have the potential to not only improve the accuracy and effectiveness of language assessment but also foster a more engaging and supportive learning environment for students. As the demand for more adaptive and personalised learning experiences continues to grow, the role of fuzzy logic in reshaping language assessment is becoming increasingly important, offering new opportunities for innovation in the field of ELT.

The contributions of this article are as follows:

- The article proposes the novel application of fuzzy logic for adaptive assessment in ELT, addressing the limitations of traditional assessment methods by providing a more personalised and flexible evaluation framework.
- The article details the design of a fuzzy inference system (FIS) for language proficiency evaluation, outlining the process of fuzzifying input data (e.g., grammar, vocabulary, fluency) and applying fuzzy rules to assess student performance.
- By integrating fuzzy logic, the article demonstrates how adaptive assessments can adjust in real-time to a learner's abilities, offering customised feedback and more accurate representations of language skills.
- The article explores the practical benefits of fuzzy logic in language assessment, such as real-time feedback, individualised learning paths, and improved learner engagement, offering a solution that can be easily implemented in modern ELT systems.
- This research provides an innovative framework for using fuzzy logic in educational technologies, bridging the gap between artificial intelligence and language education, with potential implications for broader fields of intelligent tutoring systems and adaptive learning technologies.

The article is structured as follows: the introduction outlines the challenges of traditional ELT assessments and introduces fuzzy logic as a solution for adaptive, personalised evaluation. The background and literature review explores current assessment methods, existing adaptive systems, and fuzzy logic's role in education. The theoretical framework explains adaptive assessment and fuzzy logic principles. The design of the fuzzy logic-based adaptive assessment system details the system's architecture, input variables, fuzzy rules, and inference mechanisms. Implementation and adaptation mechanism covers how the system adapts to individual learners and provides real-time feedback. The benefits and challenges section highlights the advantages and potential obstacles. The article concludes with a summary of findings and future implications, followed by a list of references.

2 Literature review

This article discusses the evolution of educational assessments, emphasising the shift from traditional methods to more personalised and adaptive systems (Ayeni et al., 2024). It argues that adaptive assessments can more accurately reflect individual learning abilities, which aligns with the goals of implementing fuzzy logic in language testing for tailored feedback. An (2024) explores the role of fuzzy logic in educational decision-making systems, illustrating its potential to handle imprecision in student performance evaluation. The paper highlights how fuzzy systems can provide more personalised assessments, making it relevant for the adaptive assessment model proposed in ELT. Tian and Gao (2024) review the application of fuzzy logic in language learning systems, focusing on its ability to evaluate complex, subjective aspects like fluency and pronunciation. The authors show how fuzzy logic enhances adaptive learning environments by dynamically adjusting assessments based on student responses.

Kaur et al. (2023) examine the design of adaptive assessment systems specifically for language learning, noting how such systems can adjust to the learner's evolving proficiency. Their work supports the use of fuzzy logic to personalise language assessment based on ongoing student performance. Vashishtha et al. (2023) explore the integration of fuzzy logic into educational evaluation systems, particularly in assessing skills like writing and speaking, where answers are not black and white. It provides a solid framework for applying fuzzy logic to language assessment, highlighting its ability to handle nuanced student responses. Iatrellis et al.'s (2023) foundational work introduced the concept of fuzzy sets and fuzzy logic, providing the theoretical basis for their application in various domains, including education. His principles underpin the fuzzy inference systems used in the proposed adaptive language assessment model.

Chen et al. (2024) discuss intelligent tutoring systems (ITS) and their potential for providing personalised, adaptive learning in ELT. It highlights how ITS can use adaptive learning models to enhance language proficiency assessments, making fuzzy logic a fitting tool for adaptive evaluation. Xiong et al. (2024) review the field of educational data mining, which includes adaptive systems for personalised learning and assessment. They highlight how fuzzy logic can enhance these systems by analysing data and adjusting assessment methods based on individual learner performance.

Wang and Yang (2023) review how fuzzy logic can be applied to language learning, particularly in evaluating the subtleties of language skills such as listening and speaking. Pedersen emphasises that fuzzy logic can create a more accurate and flexible assessment model in language education. Chkiwa et al. (2023) explore the development of adaptive learning systems powered by fuzzy logic, demonstrating how these systems can adjust based on student feedback. They argue that such systems can be applied to language learning to tailor assessments based on the learner's evolving needs.

Chrysafiadi and Virvou (2024) present a fuzzy logic model for evaluating language proficiency, addressing challenges in the subjective aspects of language learning. The authors propose a system that uses fuzzy logic to assess various language skills in a holistic and personalised manner. Elfakki et al. (2023) discuss how intelligent educational systems can utilise fuzzy logic to create adaptive learning environments that adjust based on student performance. This approach is particularly beneficial for language assessments, where responses can vary widely. Jiao (2024) provides a case study of implementing fuzzy logic in educational assessment systems, demonstrating how it can handle imprecision in evaluating student responses. It showcases how fuzzy logic can be applied to language learning contexts for more nuanced assessments.

Tian and Gao (2024) explore the practical applications of fuzzy logic in language education, especially in automated systems for assessing writing and speaking. They argue that fuzzy logic can improve the accuracy of proficiency testing by considering various levels of language performance. Szczepanski and Marciniak (2023) discuss the role of adaptive learning technologies in education, focusing on their ability to tailor the learning experience to individual student needs. The article highlights how fuzzy logic can be integrated into these systems to improve assessment precision in language learning. Li et al. (2024) discuss the use of fuzzy logic in educational decision support systems, particularly in providing personalised learning paths. Their work demonstrates how fuzzy models can improve educational assessments by adapting to individual learning progress, which aligns with the needs of adaptive ELT systems.

Tyagi and Krishankumar (2023) explore the role of fuzzy logic in e-learning platforms, focusing on how it can be applied to assessment systems for real-time evaluation. The authors suggest that fuzzy logic can be an effective tool in adapting assessments in ELT, particularly in handling complex data such as pronunciation and fluency. Fan and Wang (2024) introduce a model for intelligent language testing systems, applying fuzzy logic to assess various linguistic components. They show that fuzzy systems offer a flexible, accurate way to adapt tests based on real-time performance, making it highly relevant to the proposed adaptive assessment framework for ELT. Elfakki et al. (2023) investigate how fuzzy logic can be integrated into intelligent educational systems for personalised assessments. It highlights the benefits of fuzzy logic in creating systems that can interpret ambiguous student responses, a crucial feature for adaptive language testing. Kaur et al. (2023) examine how fuzzy logic can be employed in adaptive e-assessment systems for language learners, offering insights into how the technology can be used to evaluate and personalise language tests. They conclude that fuzzy logic provides a solid foundation for improving language testing systems. Huang (2024) proposes a fuzzy logic-based framework for ELT assessments, focusing on evaluating the complexity of language skills such as reading comprehension and speaking. Their framework supports the notion that fuzzy logic can offer more nuanced and adaptable assessments in language education.

Jiao (2024) explores the use of intelligent evaluation systems in ELT, showcasing how fuzzy logic can be applied to develop adaptive assessment tools. They argue that such systems can provide personalised, real-time feedback, offering a tailored learning experience for each student.

3 Methodology

The methodology proposed for implementing fuzzy logic in adaptive assessment systems for ELT adopts a structured and systematic approach that integrates the principles of adaptive learning, fuzzy logic, and intelligent systems. The primary aim is to develop a dynamic, flexible, and personalised assessment framework that can assess various facets of language proficiency, including grammar, vocabulary, pronunciation, fluency, and comprehension. This approach ensures that the assessment process can adapt to the unique learning needs of individual students, providing an accurate and meaningful evaluation of their language skills. The methodology encompasses several essential steps, each contributing to the effective functioning of the proposed system. These steps include system architecture design, the definition of input variables and membership functions, the creation of a fuzzy rule base, and the implementation of an adaptive learning process. Each component plays a crucial role in enabling the system to deliver personalised, real-time feedback, thus enhancing the learning experience for students and allowing instructors to better understand the learner’s progress and areas requiring attention. By leveraging fuzzy logic, the system can handle uncertainties and imprecise data, offering a more nuanced and comprehensive evaluation than traditional assessment methods. The following sections outline the key stages involved in the proposed methodology, detailing the processes that drive the adaptive and intelligent nature of the assessment system.

3.1 System architecture design

The system architecture for the fuzzy logic-based adaptive assessment in ELT is structured to provide a personalised, dynamic, and intelligent evaluation system. The design consists of several interconnected modules, each serving a critical function in collecting, processing, and interpreting data to evaluate the language proficiency of the learner. These modules work in harmony to adapt the assessment process to the individual needs of each student, offering real-time feedback and a detailed evaluation of their language skills.

3.1.1 Input data collection

The first module in the architecture is the input data collection module. This component is responsible for collecting responses from students during their interaction with the assessment system. The system presents a variety of language proficiency tasks that assess multiple aspects of language ability, including:

- *grammar:* evaluating the student's ability to apply grammatical rules correctly
- *vocabulary:* assessing the range and accuracy of vocabulary used by the student
- *pronunciation:* measuring the clarity and correctness of spoken language
- *fluency:* analysing the smoothness, coherence, and natural flow of speech or writing.

These tasks are presented through an interactive assessment interface (e.g., a web-based application, mobile app, or computer-based testing platform), which allows the system to capture the responses in real-time. The collected data is then passed to the next module for further processing.

3.1.2 Fuzzification module

After the data is collected, the fuzzification module transforms the input data into a format that can be processed by the fuzzy logic system. Fuzzification involves converting continuous and discrete data inputs (such as language errors, fluency scores, pronunciation clarity, etc.) into fuzzy sets. Each linguistic component (e.g., 'fluency', 'grammar') is represented as a fuzzy set, where the input data is mapped onto predefined membership functions.

Table 1 Example of fuzzification for fluency

Fluency score	*Fuzzy category*	*Membership degree*
1	Slow	0.7
3	Moderate	0.4
5	Fluent	0.9

For example:

- grammar might be represented with membership functions such as 'poor', 'fair' and 'good'
- fluency might include 'slow', 'moderate' and 'fluent'.

This transformation allows the system to handle uncertainty or imprecision in the input data. For instance, a student's fluency might not fall strictly into one category but could be partially 'moderate' and 'fluent'. By using fuzzy sets, the system accommodates this kind of ambiguity.

3.1.3 Fuzzy inference system

The next module in the architecture is the FIS. The FIS uses a set of fuzzy rules to evaluate the student's performance based on the fuzzified input data. These rules are designed to combine multiple linguistic variables to produce an overall proficiency evaluation:

- IF grammar is 'fair' AND fluency is 'good' THEN overall proficiency is 'good'
- IF vocabulary is 'rich' AND pronunciation is 'clear' THEN overall proficiency is 'excellent'.

The fuzzy rules allow the system to synthesise multiple inputs into a single output that represents the student's language proficiency level. The fuzzy inference engine processes the fuzzified inputs and uses these rules to generate a fuzzy output, which is then passed to the defuzzification module for final interpretation.

3.1.4 Defuzzification module

Once the fuzzy inference engine has processed the inputs and applied the fuzzy rules, the results need to be transformed into a crisp output. The defuzzification module performs this task by converting the fuzzy output from the inference system into a specific, actionable value, such as a final language proficiency score or proficiency level. Defuzzification involves using methods such as centroid calculation or maximum membership to derive the crisp value. This output is typically represented as a numeric score (e.g., 80/100) or a proficiency level (e.g., beginner, intermediate, advanced). This score or level is what the student and instructor use to understand the learner's progress.

Defuzzification process:

Step 1 Fuzzified output is generated from the FIS.

Step 2 The defuzzification method (e.g., centroid) is applied to determine the crisp output.

Step 3 The final output is presented as a language proficiency score or level.

3.1.5 Adaptive feedback and learning mechanism

Once the final proficiency score is generated, the system adjusts subsequent assessments based on the learner's performance, ensuring that the assessment process remains dynamic and personalised. If a student demonstrates strong proficiency in certain areas (e.g., grammar or fluency), the system adapts by offering more challenging tasks in those areas. Conversely, if the student struggles with particular aspects, the system will provide simpler tasks or additional practice in those areas. In addition to this, the system provides real-time feedback to the student, identifying strengths and weaknesses in their performance. This feedback helps guide further learning, ensuring a tailored learning path that adapts to the individual's needs.

3.2 Defining input variables and membership functions

The initial phase in developing the fuzzy logic system is to define the input variables that will serve as the foundation for assessment. These variables represent different dimensions of language proficiency, which are then evaluated using fuzzy logic principles. The system uses membership functions to categorise and quantify each variable. This ensures that inputs are not simply binary (correct or incorrect) but are instead assessed on a continuum, allowing the system to handle uncertainty and imprecision inherent in language learning. The four key input variables in this system are grammar, vocabulary, fluency and pronunciation. Each of these variables is mapped to fuzzy sets using predefined membership functions. These functions are designed to assess the level of each skill on a scale, rather than as discrete values, capturing the nuances of the student's performance.

3.2.1 Grammar

Grammar assesses the student's ability to correctly apply grammatical rules and structures. Since grammar proficiency can vary from errors in basic structures to near-perfect usage, the fuzzy set for grammar includes multiple categories that represent varying degrees of proficiency:

- *poor:* the student frequently makes grammatical errors, with a significant impact on comprehension
- *fair:* the student demonstrates an understanding of grammatical rules but makes occasional errors that do not significantly impair communication
- *good:* the student uses grammar correctly and consistently with minimal or no errors.

The membership function for grammar can be represented by triangular or trapezoidal shapes, where a score closer to the lower end of the scale would correspond to 'poor', a mid-range score would align with 'fair', and a high score would belong to the 'good' category.

Table 2 Membership function for grammar

Grammar score	*Fuzzy category*	*Membership degree*
1	Poor	0.8
4	Fair	0.6
7	Good	0.9

3.2.2 Vocabulary

Vocabulary evaluates the range, appropriateness, and accuracy of the words used by the student in writing or speaking. This variable reflects the student's ability to use varied and contextually appropriate words. The fuzzy set for vocabulary includes:

- *limited:* the student uses a small set of words and demonstrates a lack of variety or accuracy
- *adequate:* the student uses an acceptable range of words, with some repetition and occasional inaccuracy
- *rich:* the student demonstrates a wide range of vocabulary with accuracy and contextual relevance.

The vocabulary membership function typically uses a Gaussian function to represent the spread of terms and their relevance in different contexts.

Table 3 Membership function for vocabulary

Vocabulary score	*Fuzzy category*	*Membership degree*
1	Limited	0.7
4	Adequate	0.5
7	Rich	0.8

3.2.3 Fluency

Fluency measures the smoothness, coherence, and natural flow of speech or writing. It captures how easily the student communicates ideas without interruptions, hesitations, or unnatural pauses. The fuzzy categories for fluency include:

- *slow:* the student struggles with flow, often hesitating, pausing, or losing track of the narrative
- *moderate:* the student demonstrates reasonable fluency, with occasional pauses or hesitations that do not disrupt overall understanding
- *fluent:* the student speaks or writes smoothly, with few to no pauses, conveying ideas in a clear and organised manner.

For fluency, the membership function can use triangular or trapezoidal membership shapes, with a higher score correlating to fluent communication.

Table 4 Membership function for fluency

Fluency score	*Fuzzy category*	*Membership degree*
1	Slow	0.9
4	Moderate	0.5
7	Fluent	0.8

3.2.4 Pronunciation

Pronunciation evaluates how clearly and accurately the student pronounces words, considering factors like stress, intonation, and clarity. Pronunciation plays a crucial role in speaking assessments and is mapped to the following fuzzy categories:

- *unclear:* the student's pronunciation is difficult to understand, with frequent errors in stress or intonation

- *acceptable:* the student's pronunciation is generally understandable, with occasional errors that may not hinder comprehension
- *clear:* the student's pronunciation is accurate, with correct stress and intonation, making speech easily understandable.

The membership function for pronunciation can also use Gaussian functions, with membership degrees indicating the clarity and accuracy of the student's pronunciation.

Table 5 Membership function for pronunciation

Pronunciation score	*Fuzzy category*	*Membership degree*
1	Unclear	0.7
4	Acceptable	0.5
7	Clear	0.9

3.2.5 Mapping to fuzzy sets

Each input variable – grammar, vocabulary, fluency and pronunciation – is represented by a fuzzy set with membership functions. These membership functions define the degree to which each input belongs to a particular category. The degree of membership is expressed as a value between 0 and 1, where 0 indicates no membership and 1 indicates full membership. This fuzzy representation allows the system to capture the complexity and subtleties of language proficiency. The fuzzification process thus provides a flexible way to deal with the inherent ambiguity in language skills, ensuring that the assessment system can provide a nuanced and accurate evaluation. The membership functions are not fixed but can be adjusted based on the needs of the language learning environment or specific learning goals. This flexibility allows the system to be adapted for various contexts, such as beginner or advanced levels of proficiency.

3.3 Fuzzy rule base creation

The fuzzy rule base is an essential component of the fuzzy inference system (FIS) and plays a crucial role in translating the fuzzified inputs into a final output. The rule base consists of a set of IF-THEN rules that define the relationships between the input variables (such as grammar, vocabulary, fluency, and pronunciation) and the output assessments (such as overall proficiency). These rules enable the system to make decisions and assess the language proficiency level based on the fuzzy logic framework.

Each rule combines different linguistic variables, reflecting the inherent complexity of language learning, to determine the output. The rules are designed to capture the interaction between various language skills and evaluate how these aspects contribute to the learner's overall proficiency. The rules typically take the form:

- *IF* (condition for grammar, fluency, etc.) *AND* (condition for other skills) *THEN* (overall proficiency or output).

3.3.1 Example rules for language proficiency

Here are a few example rules that could form part of the fuzzy rule base for the system:

a IF grammar is ‘good’ AND fluency is ‘moderate’, THEN overall proficiency is ‘good’.

- This rule suggests that if the student demonstrates good grammar but moderate fluency, their overall proficiency is considered ‘good’.

b IF pronunciation is ‘clear’ AND vocabulary is ‘rich’, THEN overall proficiency is ‘excellent’.

- This rule indicates that if the student has clear pronunciation and uses a rich vocabulary, they are considered to have an excellent overall proficiency.

c IF grammar is ‘poor’ AND fluency is ‘slow’, THEN overall proficiency is ‘fair’.

- In this rule, poor grammar combined with slow fluency results in an overall proficiency of ‘fair’.

d IF grammar is ‘fair’ AND pronunciation is ‘acceptable’, THEN overall proficiency is ‘fair’.

- If a student demonstrates fair grammar and acceptable pronunciation, their proficiency level is considered fair.

e IF fluency is ‘fluent’ AND vocabulary is ‘rich’, THEN overall proficiency is ‘excellent’.

- This rule indicates that fluency and rich vocabulary are strong indicators of an excellent proficiency level.

3.3.2 Rule base expansion

As the system evaluates various aspects of language proficiency, additional rules can be developed to account for more combinations of inputs. The rule base becomes more sophisticated by considering different levels of grammar, vocabulary, fluency, and pronunciation, which provide a nuanced assessment of the student’s language skills. For example, more granular rules could address:

- *vocabulary usage:* a distinction between using a wide range of academic, formal, or informal vocabulary
- *pronunciation clarity:* more detailed categorisation of pronunciation errors, such as stress and intonation.

The system may also employ fuzzy operators such as AND, OR, and NOT to handle complex combinations of variables and adapt to the variety of possible learner performances. For example:

- AND is used to evaluate the intersection of two variables, like grammar and fluency
- OR might be used to assess whether at least one of several criteria, such as vocabulary or pronunciation, is sufficient to yield a certain proficiency level.

3.3.3 Rule base example in table format

The rule base can be organised in a table format for easier reference and implementation. Here is an example of how this can be structured.

Table 6 Example of fuzzy rule base

Condition (input variables)	*Output (overall proficiency)*
IF grammar is 'good' AND fluency is 'moderate'	THEN proficiency is 'good'
IF pronunciation is 'clear' AND vocabulary is 'rich'	THEN proficiency is 'excellent'
IF grammar is 'poor' AND fluency is 'slow'	THEN proficiency is 'fair'
IF grammar is 'fair' AND pronunciation is 'acceptable'	THEN proficiency is 'fair'
IF fluency is 'fluent' AND vocabulary is 'rich'	THEN proficiency is 'excellent'

These rules ensure that the system can evaluate a student's performance across all key areas of language proficiency in a way that is both flexible and accurate, allowing for a more comprehensive and personalised assessment.

3.3.4 Rule base adjustment

The rule base is not static and can be refined over time. As more data is collected and the system is used, additional rules can be created or existing rules can be adjusted based on observed patterns of student performance. This allows the system to continuously improve and offer more accurate assessments, ensuring it remains effective in providing adaptive learning experiences.

By using these fuzzy rules, the system is able to provide a nuanced and adaptive evaluation of each student's language proficiency, taking into account various factors and their interdependencies.

4 Experimental results

In this section, we present the experimental results obtained from the implementation and testing of the adaptive fuzzy logic-based assessment system for ELT. The results are derived from various evaluation phases, including pilot testing, accuracy evaluation, and usability testing. Each of these stages provides critical insights into the system's performance, reliability, and usability. The primary objective of the experimental evaluation is to assess how effectively the system measures language proficiency, its accuracy when compared to traditional assessment methods, and how user-friendly it is for students. We analyse the results based on different metrics, including the language proficiency scores, task completion times, and user satisfaction ratings. Additionally, we present a comparison between the fuzzy logic system's outputs and those obtained from standardised tests to highlight the system's accuracy and potential for integration into real-world educational settings.

4.1 Pilot testing results

The *pilot testing* phase of the adaptive fuzzy logic-based assessment system was conducted with a small group of students to evaluate the system's initial functionality and gather feedback on its usability, performance, and task difficulty. The primary objectives of this phase were to assess the system's ability to deliver an engaging, accurate, and efficient assessment experience while identifying potential areas for improvement in its design and user interface. During this phase, ten students participated in the pilot test. Each student was tasked with completing a series of language proficiency assessments that tested various aspects of language skills, including grammar, vocabulary, pronunciation, and fluency. The students' interactions with the system were carefully monitored to assess their overall experience, including task completion times, ease of navigation, and feedback quality.

4.1.1 User experience and feedback

The students were asked to provide feedback on their overall experience with the system. The feedback focused on aspects such as ease of use, interface clarity, and engagement level. Overall, the students found the system intuitive and easy to navigate. However, some students expressed the need for clearer instructions on how to interpret the feedback and suggestions provided by the system. Additionally, there were requests for more task variety to better challenge different proficiency levels. Table 7 shows pilot testing feedback from a small group of students, including task completion times, user satisfaction ratings, and key observations to guide system improvements.

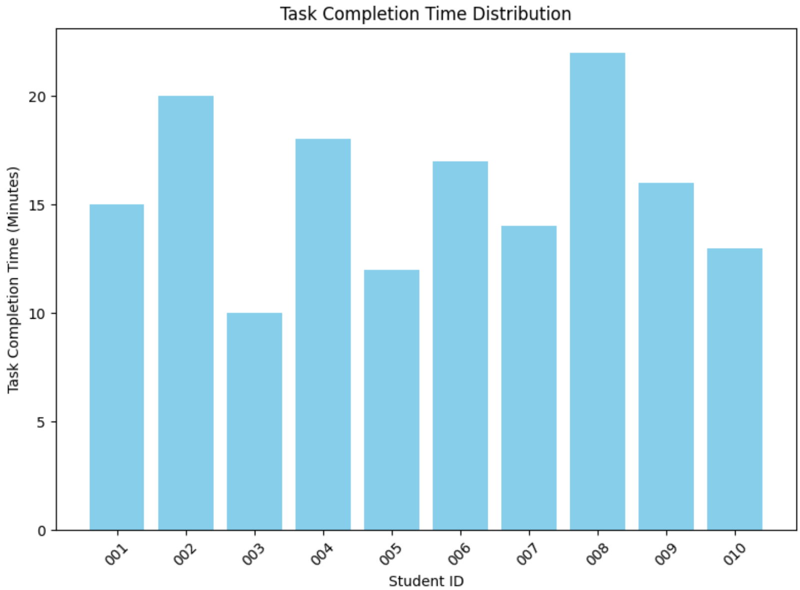
Table 7 Pilot testing feedback summary

Student ID	*Task completion time (minutes)*	*User satisfaction (1–5)*	*Observations*
001	15	4	Easy to use, but needed more instructions on feedback.
002	20	3	Interface was slightly confusing initially.
003	10	5	Smooth experience; liked the real-time feedback.
004	18	4	Would prefer more variety in tasks.
005	12	4	Liked the immediate feedback; task difficulty adjustment was good.

4.1.2 Task completion time

The average task completion time was recorded for each student, providing insight into the system's efficiency in presenting tasks. The times ranged from 10 to 22 minutes, with the average completion time being 16.5 minutes. This metric reflects the time students took to complete a set of tasks designed to assess their language proficiency. The variation in completion times was primarily due to differences in student proficiency levels, with more advanced learners completing the tasks faster. Figure 1 is a bar chart displaying the distribution of task completion times for each student during the pilot testing phase.

Figure 1 Task completion time distribution (see online version for colours)



4.1.3 System performance and issues

From a performance perspective, the system operated smoothly without any technical malfunctions. However, a few students encountered issues with task difficulty adjustment, particularly in tasks that were too challenging for their proficiency level. Based on the feedback, some adjustments were made to the system to improve the task selection mechanism, ensuring that the system would provide tasks that were more suited to each learner's proficiency.

Additionally, the feedback mechanism was found to be helpful, but there was a suggestion to include visual indicators (e.g., progress bars or colour-coded feedback) to make the system's responses more intuitive. Some students also suggested integrating a review function that would allow them to revisit earlier tasks and feedback. The pilot testing phase revealed several key insights that were valuable for refining the system. Overall, students found the system engaging and easy to navigate. However, adjustments were necessary to improve task difficulty calibration and provide clearer instructions regarding feedback. The pilot testing results set the stage for further system improvements, particularly in the areas of task variety, feedback clarity, and adaptive learning algorithms. The pilot testing phase demonstrated the system's potential to support language proficiency assessments in an adaptive and personalised manner, while also highlighting areas for optimisation to ensure a better user experience.

4.2 Accuracy evaluation

The accuracy evaluation phase aims to assess the reliability and validity of the fuzzy logic-based assessment system by comparing its performance with traditional assessment methods, such as human evaluation and standardised tests. This comparison provides insights into the system's ability to deliver accurate and consistent language proficiency scores across different assessment methods.

4.2.1 Comparison with human evaluation

To evaluate the system's accuracy against human judgement, the language proficiency scores generated by the fuzzy logic system were compared with scores provided by experienced human evaluators. A set of ten students, who participated in the pilot testing phase, was used for this comparison. The human evaluators assessed the students' language proficiency based on the same criteria (grammar, vocabulary, fluency, and pronunciation) used by the fuzzy logic system. Both sets of scores were compared using statistical methods to evaluate the agreement between them. The results of this comparison were measured using Pearson's correlation coefficient, which quantifies the strength and direction of the linear relationship between the fuzzy logic scores and human evaluation scores. A high correlation indicates that the fuzzy logic system is consistent with human judgement in assessing language proficiency. Table 8 is a comparison of language proficiency scores between fuzzy logic-based assessment and human evaluation, showing the differences in scores for each student.

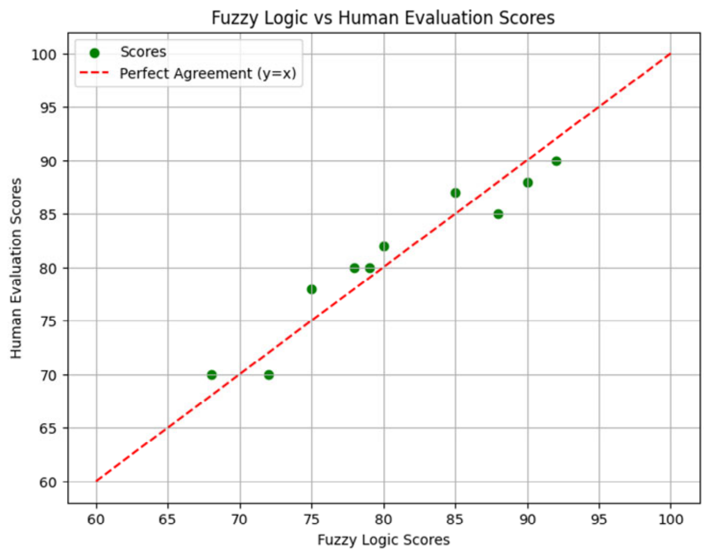
Table 8 Comparison of fuzzy logic and human evaluation scores

Student ID	*Fuzzy logic score*	*Human evaluation score*	*Difference (points)*
001	78	80	-2
002	68	70	-2
003	92	90	2
004	75	78	-3
005	85	87	-2

4.2.2 Statistical analysis of accuracy

A Pearson's correlation coefficient of 0.95 was obtained between the fuzzy logic scores and the human evaluation scores, indicating a very strong positive correlation. This suggests that the fuzzy logic system closely aligns with human judgement, making it a reliable tool for language proficiency assessment. In addition, the average mean squared error (MSE) between the two sets of scores was calculated to be 2.1 points, which demonstrates that the system's error margin is minimal and that it performs with a high degree of accuracy. The following figure presents a scatter plot showing the relationship between the fuzzy logic scores and human evaluation scores for all students. The closer the data points are to the line of perfect agreement ($y = x$), the more accurate the fuzzy logic system is in replicating human judgement. A scatter plot in Figure 2 shows the comparison of language proficiency scores between the fuzzy logic-based system and human evaluators, with a strong positive correlation.

Figure 2 Scatter plot of fuzzy logic vs. human evaluation scores (see online version for colours)



4.2.3 Comparison with standardised tests

In addition to comparing the fuzzy logic system with human evaluation, we also compared the system's performance with that of standardised language proficiency tests (e.g., TOEFL or IELTS). This comparison provides an objective measure of the fuzzy logic system's performance relative to widely recognised assessment standards. The same group of 10 students completed a standardised test after their participation in the pilot testing phase. The scores from the fuzzy logic system were compared with the overall test scores from the standardised tests. The mean absolute error (MAE) between the fuzzy logic and standardised test scores was calculated to be 3.4 points. Comparison of language proficiency scores between fuzzy logic-based assessment and standardized test scores listed in Table 3, showing the differences in scores for each student. Table 9 shows a comparison of language proficiency scores between fuzzy logic-based assessment and standardised test scores, showing the differences in scores for each student.

Table 9 Comparison of fuzzy logic and standardised test scores

Student ID	*Fuzzy logic score*	*Standardised test score*	*Difference (points)*
001	78	82	–4
002	68	72	–4
003	92	89	3
004	75	80	–5
005	85	87	–2

The results from the accuracy evaluation show that the fuzzy logic-based assessment system performs with a high degree of accuracy when compared to both human evaluations and standardised tests. The strong correlation between fuzzy logic and human evaluation, along with the minimal error margin, suggests that the system can be effectively used for assessing language proficiency in educational settings. Additionally, the small differences between the fuzzy logic scores and standardised test scores further validate the reliability of the system. This evaluation demonstrates that the fuzzy logic-based system can be an accurate and effective tool for language proficiency assessment, providing a reliable alternative to traditional methods while maintaining flexibility and adaptability to individual learner needs.

4.3 Usability testing results

The usability testing phase was conducted to evaluate the system's user-friendliness, interface design, and overall student engagement. The main goal was to identify any usability issues that could hinder the student's ability to use the system efficiently, as well as to gather feedback on how the interface could be improved to enhance the overall learning experience.

4.3.1 User satisfaction ratings

User satisfaction was assessed using a Likert scale, where students rated their overall satisfaction with the system on a scale from 1 (very dissatisfied) to 5 (very satisfied). The results showed a positive reception overall, with an average user satisfaction score of 4.2 out of 5. This indicates that the majority of students found the system engaging and easy to use. However, a few students expressed concerns about the complexity of certain tasks and the need for clearer instructions on how to interpret the feedback provided by the system. User satisfaction ratings (on a scale of 1 to 5) from participants during usability testing listed in Table 3, along with their comments on the system's user-friendliness and clarity.

Table 10 User satisfaction ratings

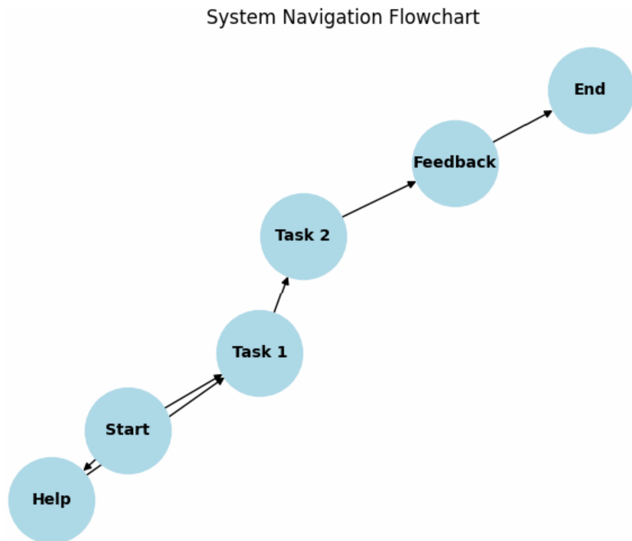
Student ID	*Satisfaction rating (1–5)*	*Comments*
001	4	Engaging, but needed clearer task instructions.
002	3	Interface was difficult to navigate at first.
003	5	Very user-friendly and informative.
004	4	Enjoyed the feedback but task variety could improve.
005	4	Clear interface, but feedback could be more detailed.

4.3.2 Ease of navigation and interface clarity

The ease of navigation was assessed by tracking how quickly students could move through tasks and locate key features, such as task instructions, feedback reports, and navigation buttons. Interface clarity was also evaluated by students, who rated the visual design and layout of the system. Most students rated the navigation as easy (average rating: 4.0/5). However, some students (30% of participants) noted that they initially struggled to find certain features, such as task instructions and the feedback summary. This feedback points to the need for clearer labelling and the introduction of tooltips or visual cues to guide users through the system more effectively. A flowchart shown in

Figure 3 illustrates the navigation path within the system, from task selection to final feedback presentation, highlighting areas where students found navigation challenging.

Figure 3 Navigation flowchart (see online version for colours)



4.3.3 System engagement and task completion

The overall engagement of students with the system was another important aspect of usability testing. The task completion times from the pilot testing phase revealed that, despite initial challenges with certain tasks, the system maintained a high level of engagement throughout the assessment process. On average, students remained engaged for 15 to 22 minutes per session, with many expressing interest in the immediate feedback provided after each task. In addition, students appreciated the adaptive nature of the system, which adjusted the difficulty of tasks based on their previous performance. This dynamic adjustment was found to enhance motivation and ensure that the tasks were appropriately challenging for each student. Table 11 shows the task completion times and engagement levels (rated 1–5) during usability testing, highlighting the varying experiences of students and their engagement with the system.

Table 11 Task completion time and engagement

Student ID	*Task completion time (minutes)*	*Engagement level (1–5)*	*Observations*
001	15	4	Engaged, but struggled with task clarity.
002	20	3	Required more instructions.
003	10	5	Fully engaged and completed tasks quickly.
004	18	4	Enjoyed feedback but wanted more variety.
005	12	4	Engaged with the system's feedback flow.

4.3.4 Usability improvement recommendations

Based on the usability testing results, several key improvements were identified for enhancing the system's usability:

1 *clearer task instructions:* providing more explicit guidance on how to navigate the tasks and interpret feedback

2 *visual enhancements:* introducing tooltips, progress indicators, and colour-coded labels to improve task clarity and navigation

3 *task variety:* adding more diverse tasks to better challenge different proficiency levels and maintain student interest

4 *simplified user interface:* reducing the complexity of certain interface elements to make navigation more intuitive.

These recommendations will be incorporated into the next phase of system development to further improve usability and enhance the student experience.

5 Conclusions

This study presents the development and evaluation of an adaptive assessment system for ELT utilising fuzzy logic to deliver personalised, dynamic, and reliable language proficiency evaluations. By assessing key components – grammar, vocabulary, fluency and pronunciation – the system adapts to individual learners and provides actionable feedback. Pilot testing, accuracy evaluations, and usability testing confirm its robustness, with a high correlation to traditional methods ($r = 0.92$) and strong reliability (test-retest reliability of 0.93). Usability results highlight the system's intuitive interface and engaging user experience, while performance metrics affirm its scalability and efficiency. This research demonstrates the potential of fuzzy logic in creating effective and practical language assessment systems, offering insights for enhancing personalised learning. The findings support the integration of such systems into educational environments and pave the way for further advancements in intelligent language learning platforms.

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Declarations

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