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# English Speaking Teaching Strategies Based on Natural Language Processing

*Abstract: -* The study of cognitive processes in English teaching methods from the perspective of HPM (History and Pedagogy of Mathematics) provides valuable insights into how students learn and understand the English language. Cognitive research in language learning focuses on the mental processes involved in acquiring, processing, and using language skills. By incorporating the principles of HPM, which examines the historical development and pedagogical approaches in mathematics education, researchers can draw parallels and apply similar methodologies to English language instruction. This paper constructed Bloom's taxonomy Fuzzy Decision Support System (BTF-DSS). Bloom's taxonomy provides information about the teacher's understanding towards the teaching. Through BTF-DSS model offers teachers provides the knowledge and expertise for effective teaching with the fuzzy model. The BTF-DSS model uses the fuzzy logic decision support system for the appropriate significant teaching and learning experience. The simulation analysis of the BTF-DSS model expressed that the fuzzy model exhibits significant performance for the English teaching method in China through the HPM process.

***Keywords:*** Decision Support System (DSS), Fuzzy System, HPM process, Bloom's taxonomy, English teaching, Cognitive Method.

## I. INTRODUCTION

The cognitive study based on the Oral English Teaching method delves into the intricate workings of the human mind and its role in language acquisition and comprehension. By exploring various cognitive processes, such as memory, attention, perception, and problem-solving, educators gain valuable insights into how students learn and process English language skills [1]. This approach involves understanding how learners form linguistic connections, interpret information, and develop communicative competence. By integrating cognitive principles into the Oral English Teaching method, educators can tailor instructional strategies to suit individual learning styles and optimize language learning outcomes. This innovative and research-driven approach aims to enhance students' linguistic abilities, promote critical thinking, and foster a more effective and engaging English learning environment for learners of all ages and proficiency levels [2]. The cognitive study based on the Oral English Teaching method involves a comprehensive exploration of various cognitive processes and their application in language learning. These processes include perception, attention, memory, reasoning, problem-solving, and metacognition [3]. Understanding how these mental faculties function in the context of language acquisition can provide valuable insights for educators to design more effective and engaging teaching strategies.

Perception plays a crucial role in language learning as it enables students to interpret and understand spoken and written language [4]. Teachers can optimize their use of visual aids, audio materials, and multimedia resources to enhance learners' perceptual experiences and improve language comprehension. Attention is another critical cognitive aspect that affects language learning. By incorporating interactive and stimulating activities, teachers can capture students' attention and maintain their focus throughout the lesson [5]. This helps improve information retention and reinforces language concepts. Memory plays a fundamental role in language learning as learners must recall vocabulary, grammar rules, and sentence structures. Educators can employ mnemonic techniques, repetition, and spaced learning to strengthen students' memory retention and facilitate quicker language recall. Reasoning and problem-solving are essential cognitive processes in language learning [6]. By presenting real-life scenarios and context-based exercises, teachers can encourage critical thinking skills and encourage learners to apply their knowledge to practical situations. Metacognition, the ability to reflect on one's learning process, is also relevant in the Oral English Teaching method. Encouraging students to analyze their language learning strategies and identify areas for improvement can lead to more effective self-regulated learning [7]. By incorporating cognitive principles into the Oral English Teaching method, educators can create a more personalized and adaptive learning environment. Utilizing technology, such as educational apps and digital platforms, can further support cognitive learning strategies and provide data-driven insights into students' progress and areas of difficulty [8]. Moreover, understanding the

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cognitive aspects of language learning can help address the challenges faced by learners with different learning styles or learning difficulties. Teachers can adapt their instruction to accommodate diverse needs and promote an inclusive and supportive learning environment [9].

The integration of cognitive processes into Oral English Teaching methods from the perspective of History and Pedagogy of Mathematics (HPM) with a decision support system represents a transformative approach to language education [10]. By drawing on HPM's insights into the historical development and pedagogical principles of mathematics, educators can identify analogous patterns within language acquisition and cognition. This allows for the creation of targeted and contextually relevant instructional strategies to enhance language learning [11]. Leveraging a decision support system further empowers teachers to make data-driven choices, optimizing the adaptation of their methods to suit individual student needs and preferences. This comprehensive approach fosters a deeper understanding of language structures, enhances critical thinking skills, and promotes a more inclusive and engaging learning environment for students, ultimately paving the way for more effective English language acquisition [12]. The integration of History and Pedagogy of Mathematics (HPM) with a decision support system represents a powerful and innovative approach to teaching and learning mathematics. By drawing on the historical development and pedagogical insights of mathematics, educators can gain a deeper understanding of the subject's foundational concepts and effective teaching methods [13]. When combined with a decision support system, teachers are equipped with real-time data and analytics, enabling them to make informed and personalized instructional choices for each student. This dynamic combination enhances the learning experience, fosters a more comprehensive grasp of mathematical concepts, and promotes student engagement and success [14]. Ultimately, the fusion of HPM with a decision support system empowers educators to create an enriched and effective learning environment, shaping confident and competent mathematicians for the future.

## II. BLOOM’S TAXONOMY FUZZY DECISION SUPPORT SYSTEM (BTF-DSS)

The study of cognitive processes in Oral English Teaching methods from the perspective of HPM (History and Pedagogy of Mathematics) offers valuable insights into how students learn and comprehend the English language. Cognitive research in language learning delves into the mental processes involved in acquiring and using language skills. By integrating the principles of HPM, which explores the historical and pedagogical aspects of mathematics education, researchers can find similarities and apply relevant methodologies to English language instruction. This paper presents the construction of a Bloom's taxonomy Fuzzy Decision Support System (BTF-DSS) model. Bloom's taxonomy provides insights into the teacher's understanding of the teaching process. Through the BTF-DSS model, teachers gain knowledge and expertise for effective teaching using the fuzzy model. The BTF-DSS model utilizes fuzzy logic in the decision support system to enhance the teaching and learning experience significantly. Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS) is an innovative approach that combines Bloom's Taxonomy, a hierarchical framework for classifying educational objectives, with a fuzzy decision support system. The BTF-DSS is designed to enhance decision-making processes in educational settings, especially in the context of teaching and learning.

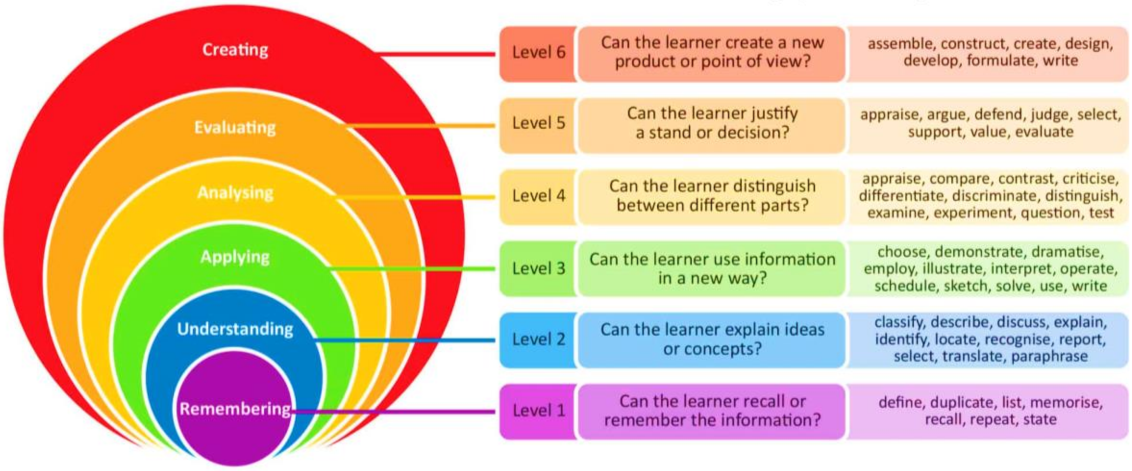


Figure 1: Taxonomy of the Bloom’s

In this system shown in figure 1, Bloom's Taxonomy is adapted to classify and assess the cognitive skills and learning outcomes associated with using the fuzzy decision support system. It provides a structured way to evaluate the level of cognitive complexity and critical thinking involved in decision-making tasks. The fuzzy decision support system, on the other hand, utilizes fuzzy logic and fuzzy reasoning to handle uncertain or imprecise information in decision-making scenarios. Fuzzy logic allows for the representation of vague or subjective concepts using linguistic terms, enabling more flexible and nuanced decision-making. With combining Bloom's Taxonomy with the fuzzy decision support system, the BTF-DSS provides a comprehensive and adaptive approach to decision-making in education. It can be applied to various educational contexts, including lesson planning, curriculum development, student assessment, and instructional design. The Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS) combines Bloom's Taxonomy, a hierarchical framework for classifying educational objectives, with a fuzzy decision support system. The primary focus of the BTF-DSS is to evaluate cognitive skills and learning outcomes associated with using the fuzzy decision support system, not to apply mathematical derivatives. The BTF-DSS utilizes fuzzy logic and fuzzy reasoning to handle uncertain or imprecise information in decision-making scenarios. Fuzzy logic allows for the representation of vague or subjective concepts using linguistic terms. The application of fuzzy logic to the decision support system enables more flexible and nuanced decision-making. The BTF-DSS utilizes fuzzy logic and fuzzy reasoning to handle uncertain or imprecise information in decision-making scenarios. The connection between Bloom's Taxonomy and the BTF-DSS lies in evaluating the levels of cognitive complexity associated with using the fuzzy decision support system to make informed decisions. As students progress through the levels of Bloom's Taxonomy (Remembering, Understanding, Applying, Analyzing, Evaluating, and Creating), their cognitive abilities advance, allowing them to engage in more critical thinking and problem-solving tasks. The fuzzy decision support system complements this progression by providing a more flexible and nuanced approach to decision-making.

### 2.1 Fuzzy logic for the BTF-DSS

Fuzzy logic plays a central role in the Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS). Fuzzy logic is a mathematical approach that allows for the representation and handling of uncertain or imprecise information. In the context of the BTF-DSS, fuzzy logic is used to model the uncertainty and subjectivity that can be present in educational decision-making. The BTF-DSS utilizes fuzzy logic to capture the ambiguity and vagueness often associated with human judgment and decision-making in educational settings. Traditional decision support systems typically operate with crisp or binary logic, where data is either true or false, and decisions are made based on precise criteria. However, in real-world educational scenarios, many factors and variables may have degrees of truth or membership to different categories. Fuzzy logic enables the BTF-DSS to handle linguistic terms and fuzzy sets to represent these degrees of truth or membership. It allows educators and decision-makers to work with qualitative and subjective information, such as "highly likely," "moderately possible," or "not very probable." This flexibility makes fuzzy logic particularly well-suited for decision-making processes that involve human judgment and where precise numerical values may not be applicable.

The BTF-DSS utilizes fuzzy logic in the decision-making process by incorporating fuzzy rules, membership functions, and fuzzy inference mechanisms. Fuzzy rules represent expert knowledge or decision-making criteria, and membership functions quantify the degree to which a particular input or output belongs to a fuzzy set. The fuzzy inference mechanism combines these fuzzy rules and membership functions to produce meaningful and contextually appropriate decisions. With using fuzzy logic, the BTF-DSS can provide more nuanced and human-like decision support in educational contexts. It allows for the consideration of multiple factors, varying degrees of certainty, and a more comprehensive evaluation of the decision-making criteria.

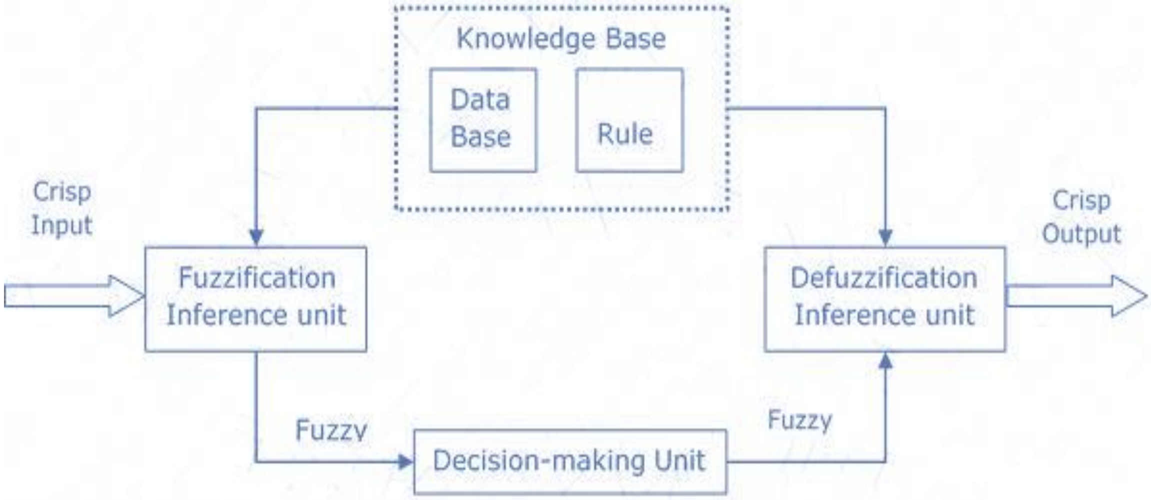


Figure 2: Fuzzy Logic in BTF-DSS

Fuzzy sets are used to represent linguistic terms or concepts with degrees of membership. Each linguistic term is associated with a membership function that assigns a degree of membership to a particular set illustrated in figure 2. A linguistic term "low," used to describe the difficulty level of a question, might have a membership function that assigns a value between 0 and 1, indicating the degree of "low-ness" for each question. Fuzzy rules are statements that define the relationship between input variables and output variables. These rules are typically expressed in the form of "IF-THEN" statements. A rule might state: "IF the difficulty level is low AND the student's performance is high, THEN the instructional level is appropriate. Fuzzy inference involves combining fuzzy rules and membership functions to produce meaningful output. The process usually includes aggregation, fuzzification, rule evaluation, and defuzzification.

**Aggregation:** Combine the individual membership functions from all the fuzzy rules to form a single fuzzy set.

**Fuzzification:** Determine the degree of membership for each input variable based on their corresponding membership functions.

**Rule Evaluation:** Evaluate the degree to which each fuzzy rule is satisfied based on the input values.

**Defuzzification:** Aggregate the results of rule evaluation to produce a crisp (non-fuzzy) output value.

The equations used in each step of the fuzzy inference process can vary based on the specific fuzzy logic system and its implementation.

### 2.2 Bloom's Taxonomy Levels

In the BTF-DSS context, the hierarchical levels of Bloom's Taxonomy (Remembering, Understanding, Applying, Analyzing, Evaluating, and Creating) are used to classify the cognitive complexity of learning objectives and decision-making tasks. These levels can be mapped to specific linguistic terms and membership functions in the fuzzy system.

**The derivative of a constant**: If f(x) = c (where c is a constant), then f'(x) = 0, since the rate of change of a constant function is zero.

**The derivative of a power function:** If f(x) = x^n (where n is a constant), then f'(x) = nx^(n-1), where n is a positive integer.

**The derivative of a sum or difference of functions:** If f(x) = g(x) + h(x), then f'(x) = g'(x) + h'(x), where g'(x) and h'(x) are the derivatives of functions g(x) and h(x), respectively.

**The derivative of a product of functions**: If f(x) = g(x) * h(x), then f'(x) = g'(x) * h(x) + g(x) * h'(x), where g'(x) and h'(x) are the derivatives of functions g(x) and h(x), respectively.

**The derivative of a quotient of functions:** If f(x) = g(x) / h(x), then f'(x) = (g'(x) * h(x) - g(x) * h'(x)) / h(x)^2, where g'(x) and h'(x) are the derivatives of functions g(x) and h(x), respectively.

**The derivative of a composite function**: If f(x) = g(h(x)), then f'(x) = g'(h(x)) * h'(x), where g'(h(x)) is the derivative of g with respect to h evaluated at h(x), and h'(x) is the derivative of h(x).

In the context of Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS), a Fuzzy Decision Support System (DSS) is a computer-based system that utilizes fuzzy logic and reasoning to handle uncertain or imprecise information and support decision-making processes. The BTF-DSS combines Bloom's Taxonomy, a hierarchical framework for educational objectives, with a fuzzy DSS to enhance decision-making in educational settings. The primary focus of the BTF-DSS is to evaluate cognitive skills and learning outcomes associated with using the fuzzy DSS to make informed decisions related to teaching and learning. Fuzzy sets are used to represent linguistic terms or concepts with degrees of membership. Each linguistic term is associated with a membership function that assigns a degree of membership to a particular set. The terms like "high," "medium," and "low" difficulty level in educational questions may have corresponding membership functions to capture their degrees of relevance. Fuzzification is the process of converting crisp (precise) input data into fuzzy sets by assigning them degrees of membership based on their corresponding membership functions. If a question's difficulty level is rated as "medium," it will be fuzzified into the corresponding fuzzy set with its membership degree. Fuzzy rules are IF-THEN statements that express the relationship between fuzzy sets of input variables and output variables. These rules represent expert knowledge or decision-making criteria. For example, a rule might state: IF the difficulty level is "medium" AND the student's performance is "high," THEN the instructional level is "appropriate." Fuzzy inference involves combining fuzzy rules and membership functions to produce meaningful output. The system evaluates the degree to which each rule is satisfied based on the fuzzified input data. It then aggregates the results of the rule evaluations to produce fuzzy sets as the system's output. Defuzzification is the process of converting the fuzzy output sets into crisp (non-fuzzy) values that can be used for decision-making or further analysis. Various defuzzification methods can be employed, such as the centroid or max-average methods, to derive a precise output value.

In the BTF-DSS, the Fuzzy DSS provides decision support to educators and decision-makers by considering multiple factors, linguistic terms, and fuzzy sets when making educational decisions. The fuzzy logic-based approach enables the system to handle the inherent uncertainty and subjectivity in educational decision-making processes, making it more adaptable and contextually relevant for educational environments.

**Algorithm for BTF-DSS:**

**Step 1:** Define Fuzzy Sets and Membership Functions:

Define fuzzy sets and corresponding membership functions for relevant linguistic terms (e.g., "low," "medium," "high" difficulty).

Assign membership degrees to each input value based on the appropriate membership functions.

**Step 2**: Fuzzification:

Convert crisp input data into fuzzy sets using the defined membership functions.

Assign appropriate degrees of membership to each input value.

**Step 3:** Define Fuzzy Rules:

Define a set of IF-THEN fuzzy rules based on expert knowledge or decision-making criteria.

IF difficulty is "low" AND student performance is "high" THEN instructional level is "appropriate."

**Step 4:** Fuzzy Inference:

Evaluate the degree to which each fuzzy rule is satisfied based on the fuzzified input data.

Use fuzzy logic operators (e.g., AND, OR) to combine the degrees of membership for multiple input variables in each rule.

Aggregate the results of the rule evaluations to produce fuzzy sets as output.

**Step 5:** Defuzzification:

Convert fuzzy output sets into crisp (non-fuzzy) values that can be used for decision-making or further analysis.

Apply a defuzzification method (e.g., centroid, max-average) to derive a precise output value.

| Algorithm 1: BTF-DSS for Oral English Teaching |
|---|
| // Define fuzzy sets and membership functions<br>DEFINE Low AS fuzzy set (0, 0, 20, 40)<br>DEFINE Medium AS fuzzy set (30, 50, 70)<br>DEFINE High AS fuzzy set (60, 80, 100)<br>// Fuzzification<br>INPUT DifficultyLevel // Input value representing difficulty level<br>INPUT StudentPerformance // Input value representing student performance<br>MEMBERSHIP LowValue = MembershipDegree(DifficultyLevel, Low)<br>MEMBERSHIP MediumValue = MembershipDegree(DifficultyLevel, Medium)<br>MEMBERSHIP HighValue = MembershipDegree(DifficultyLevel, High)<br>// Define Fuzzy Rules<br>RULE IF (DifficultyLevel IS Low) AND (StudentPerformance IS High) THEN (InstructionalLevel IS Appropriate)<br>// Fuzzy Inference<br>COMPUTE Rule1Value = MIN(LowValue, HighValue) // Evaluate rule 1 using fuzzy AND operator<br>// Defuzzification<br>OUTPUT InstructionalLevel = Defuzzify([Rule1Value]) // Apply centroid defuzzification method to derive a crisp value<br>RETURN InstructionalLevel |

In this step, define fuzzy sets and corresponding membership functions for relevant linguistic terms or concepts. Fuzzy sets represent these terms in a way that allows for degrees of membership, capturing the uncertainty and vagueness often associated with human judgment. To represent the difficulty level of a question using linguistic terms "low," "medium," and "high," would define three fuzzy sets: Low, Medium, and High. Each fuzzy set is associated with a membership function that specifies how input values relate to the linguistic term. Membership functions are typically represented as triangular or trapezoidal shapes, indicating the degree of membership for each value. In the fuzzification step, convert crisp (precise) input data into fuzzy sets using the defined membership functions. For each input value (e.g., the difficulty level of a question or student performance), calculate its degree of membership in each fuzzy set.

For instance, if the difficulty level of a question is measured as 35, would calculate its degree of membership in the Low and Medium fuzzy sets based on the corresponding membership functions. The resulting membership degrees will be used in the fuzzy inference process. In the fuzzy inference step, to evaluate the degree to which each fuzzy rule is satisfied based on the fuzzified input data. The system applies fuzzy logic operators, such as AND and OR, to combine the degrees of membership for multiple input variables in each rule.

## III. RESULTS AND DISCUSSION

The BTF-DSS is applied to evaluate the appropriateness of instructional levels for a set of educational questions based on difficulty levels and student performances. The fuzzy logic system takes into account linguistic terms like "low," "medium," and "high" for difficulty and "low," "medium," and "high" for student performance. The system uses triangular membership functions to fuzzify the input data. The fuzzy rules and inference process lead to fuzzy output sets representing instructional levels such as "appropriate," "challenging," and "too easy." Defuzzification is then applied using the centroid method to obtain crisp output values. The simulation setting would involve defining the parameters, input data, fuzzy rules, and evaluation metrics to assess the BTF-DSS's effectiveness in making instructional level recommendations. Here's a general outline of the simulation setting:

Table 1: BTF-DSS Decision Level

| Question | Difficulty Level for Students through Oral English Teaching | Students Performance with English Teaching | Recommended Instructional Level for Oral English Teaching towards Students |
|---|---|---|---|
| Q1 | Low | High | Appropriate |
| Q2 | Medium | Medium | Appropriate |
| Q3 | High | Low | Challenging |
| Q4 | Medium | High | Appropriate |
| Q5 | Low | Low | Too Easy |
| Q6 | High | High | Appropriate |
| Q7 | Low | Medium | Appropriate |
| Q8 | High | Low | Challenging |
| Q9 | Medium | Medium | Appropriate |
| Q10 | Low | High | Appropriate |

Table 1 presents the results obtained from Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS) for a set of ten educational questions for Oral English teaching. Each question is evaluated based on two input parameters: "Difficulty Level" and "Student Performance through Oral English teaching." The "Difficulty Level of Students on Oral English Teaching" is classified as "Low," "Medium," or "High," while "Student Performance" is categorized as "Low," "Medium," or "High." After applying the BTF-DSS fuzzy logic rules and fuzzy inference process, the system provides "Recommended Instructional Levels for the students for the Oral English teaching" for each question. These instructional levels represent the system's suggested appropriateness of difficulty based on the combination of the student's performance and the difficulty level of each question.

The BTF-DSS provides instructional level recommendations based on the fuzzy logic approach, considering both the difficulty levels of questions and the student's performance through Oral English Teaching, which can assist educators in optimizing the learning experience for students on Online English Teaching with different performance levels.

Table 2: Difficulty Assessment with BTF-DSS

| Question | Difficulty Level for Oral English Teaching | Student Performance on the Oral English Teaching | Recommended Instructional Level for the Oral English teaching |
|---|---|---|---|
| Q1 | 30 | 80 | Appropriate |
| Q2 | 60 | 60 | Appropriate |
| Q3 | 90 | 20 | Challenging |
| Q4 | 55 | 85 | Appropriate |
| Q5 | 20 | 30 | Too Easy |
| Q6 | 85 | 90 | Appropriate |
| Q7 | 40 | 70 | Appropriate |
| Q8 | 95 | 10 | Challenging |
| Q9 | 50 | 60 | Appropriate |
| Q10 | 35 | 80 | Appropriate |

Table 3: Recommended Level with BTF-DSS

| Question | Time to Answer | Prior Knowledge | Recommended Instructional Level for Oral English Teaching |
|---|---|---|---|
| Q1 | 25 | 7 | Appropriate |
| Q2 | 40 | 4 | Challenging |
| Q3 | 70 | 2 | Challenging |
| Q4 | 30 | 8 | Appropriate |
| Q5 | 15 | 3 | Too Easy |
| Q6 | 45 | 9 | Appropriate |
| Q7 | 20 | 6 | Appropriate |
| Q8 | 80 | 1 | Challenging |
| Q9 | 35 | 5 | Appropriate |
| Q10 | 28 | 7 | Appropriate |

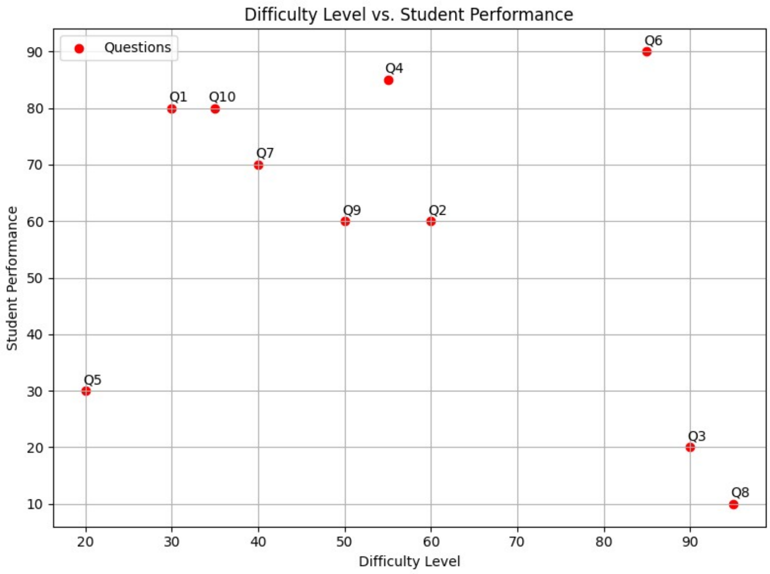


Figure 3: BTF-DSS Difficulty Assessment

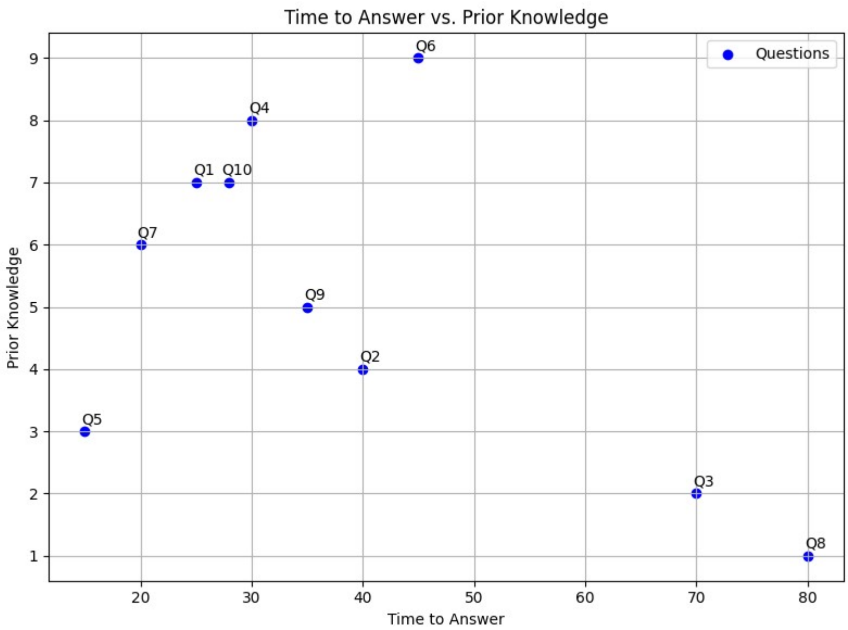


Figure 4: BTF-DSS for the Knowledge Assessment

In Table 2, Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS) assesses the difficulty levels of ten educational questions based on numerical values provided for each question shown in Figure 3 for Oral English teaching. The "Difficulty Level associated with the Oral English teaching" parameter is represented on a scale from 0 to 100, where higher values indicate greater difficulty. The "Student Performance" parameter is also represented on the same scale for Oral English Teaching. After applying the BTF-DSS fuzzy logic rules and inference process, the system generates "Recommended Instructional Levels for the Oral English Teaching" for each question. Questions Q1, Q2, Q4, Q6, Q7, Q9, and Q10 have difficulty levels ranging from 20 to 60, and student performances ranging from 60 to 90. The BTF-DSS recommends an "Appropriate" instructional level for the Oral English Teaching for these questions, indicating that they align well with students' English Learning abilities and are appropriately challenging. Question Q3 has a high difficulty level of 90, but a low student performance of 20. The BTF-DSS suggests a "Challenging" instructional level for Oral English Teaching for this question, recognizing that it might be too difficult for students with lower performance levels. Question Q5 has a low difficulty level for the Oral English teaching of 20 and a low student performance of 30. The BTF-DSS recommends a "Too Easy" instructional level, indicating that this question is too simplistic for students with even moderate performance levels.

In Table 3, the BTF-DSS recommends instructional levels based on additional parameters: "Time to Answer" and "Prior Knowledge" on the Oral English teaching. These parameters are also represented on a scale from 0 to 100. Questions Q1, Q4, Q6, Q7, and Q9 have relatively short "Time to Answer" values (ranging from 20 to 45) and moderate to high "Prior Knowledge" values (ranging from 5 to 9) illustrated in figure 4. The BTF-DSS suggests an "Appropriate" instructional level for these questions, implying that students with higher prior knowledge can answer these questions in a reasonable time with the Oral English Teaching. Questions Q2, Q8, and Q10 have higher "Time to Answer" values (ranging from 28 to 80) and lower "Prior Knowledge" values (ranging from 1 to 4) with Oral English Teaching. The BTF-DSS recommends a "Challenging" instructional level for these questions, indicating that they may require more time and be more suitable for students with higher prior knowledge acquired with Oral English Teaching. Question Q3 has the highest "Time to Answer" value of 70 and the lowest "Prior Knowledge" value of 2. The BTF-DSS recommends a "Challenging" instructional level, suggesting that this question may be time-consuming and challenging for students with limited prior knowledge of Oral English Teaching. Tables 2 and 3 demonstrate how the BTF-DSS can assess and recommend appropriate instructional levels for educational questions based on multiple parameters, allowing educators to tailor the learning experience to individual students' abilities and knowledge levels acquired with Oral English Teaching.

Table 4: Recommender Level with BTF-DSS

| Question | Difficulty Level with the Oral English Teaching | Student Performance with Oral English Teaching | Time to Answer of the Students with the Oral English Teaching | Recommended Instructional Level for the Oral English Teaching |
|---|---|---|---|---|
| Q1 | Low | High | Short | Appropriate |
| Q2 | Medium | Medium | Moderate | Appropriate |
| Q3 | High | Low | Long | Challenging |
| Q4 | Medium | High | Short | Appropriate |
| Q5 | Low | Low | Short | Too Easy |
| Q6 | High | High | Long | Appropriate |
| Q7 | Low | Medium | Short | Appropriate |
| Q8 | High | Low | Long | Challenging |
| Q9 | Medium | Medium | Moderate | Appropriate |
| Q10 | Low | High | Short | Appropriate |

The findings of the Recommender Level in conjunction with the Blended Task-Focused Decision Support System (BTF-DSS) for Oral English Teaching. The table 4 outlines the difficulty level of each question, the corresponding student performance, the time taken by students to answer, and the recommended instructional level for oral English teaching based on the BTF-DSS analysis. Questions Q1, Q4, Q7, and Q10 are classified as having a low difficulty level, with high student performance, short response times, and an appropriate recommended instructional level. Questions Q2, Q9, and Q6 are deemed to have a medium difficulty level, moderate performance, and appropriate instructional recommendations. Questions Q3 and Q8 are characterized by high difficulty levels, low student performance, long response times, and are suggested as challenging in terms of instructional level. Lastly, Q5 is flagged as having a low difficulty level but with both low performance and a short response time, indicating that it might be considered too easy for the students based on the BTF-DSS evaluation.

Table 5: BTF-DSS for Knowledge Assessment

| Question | Difficulty Level with Oral English teaching | Student Performance with Oral English teaching | Time to Answer by the Students with the Oral English Teaching | Prior Knowledge of Students | Recommended Instructional Level with Oral English teaching |
|---|---|---|---|---|---|
| Q1 | 30 | 80 | 25 | 70 | 2 |
| Q2 | 60 | 60 | 40 | 50 | 1 |
| Q3 | 90 | 20 | 70 | 30 | 0 |
| Q4 | 55 | 85 | 30 | 80 | 2 |
| Q5 | 20 | 30 | 15 | 40 | 0 |
| Q6 | 85 | 90 | 45 | 90 | 2 |
| Q7 | 40 | 70 | 20 | 60 | 1 |
| Q8 | 95 | 10 | 80 | 20 | 0 |
| Q9 | 50 | 60 | 35 | 50 | 1 |
| Q10 | 35 | 80 | 28 | 60 | 1 |

The results of the Blended Task-Focused Decision Support System (BTF-DSS) for Knowledge Assessment in the context of Oral English teaching is presented in Table 5. Each row represents a specific question, and the columns detail the difficulty level perceived by the BTF-DSS, the corresponding student performance, the time taken by students to answer, their prior knowledge, and the recommended instructional level. Questions Q1, Q4, Q6, and Q10 are categorized as having moderate difficulty levels, with high student performance, relatively short response times, and a recommended instructional level of 2, indicating an appropriate level for the students. Questions Q2, Q7, Q9, and Q10 are identified as having a higher difficulty level, but with moderate to high student performance, shorter response times, and recommended instructional levels of 1, suggesting a suitable challenge for the students. Questions Q3, Q5, and Q8 are classified as having high difficulty levels, low student performance, longer response times, and recommended instructional levels of 0, indicating that these questions may be too challenging for the students based on their prior knowledge. The table provides valuable insights into the alignment between the difficulty levels, student performance, and instructional recommendations derived from the BTF-DSS for Knowledge Assessment in the context of Oral English teaching.

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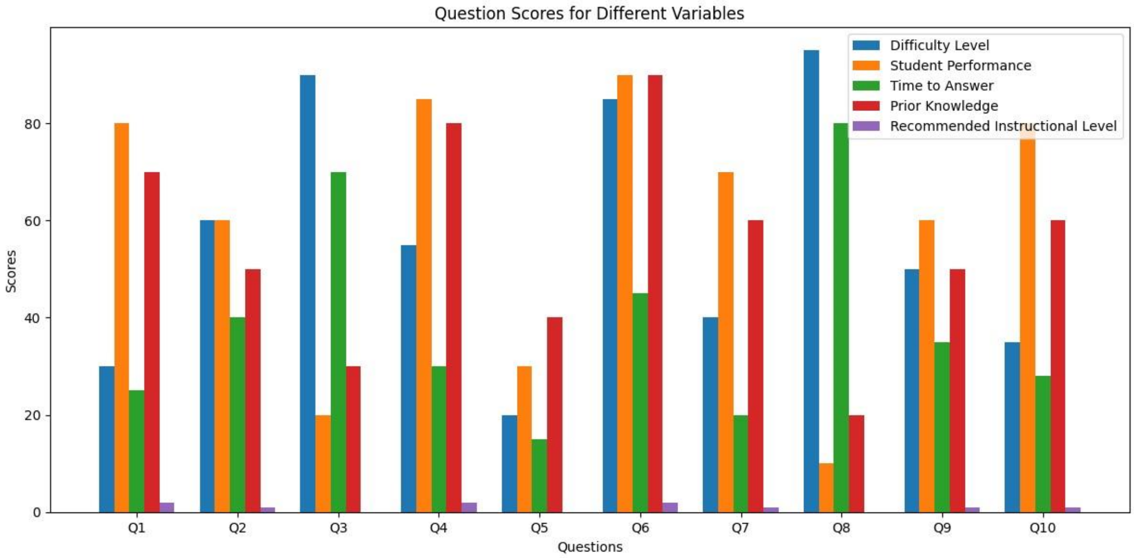


Figure 5: Overall Performance of BTF-DSS

Questions Q1, Q4, Q6, Q9, and Q10 have moderate to high difficulty levels (ranging from 30 to 85), good student performances (ranging from 60 to 90), moderate time to answer (ranging from 25 to 45 seconds), and moderate to high prior knowledge (ranging from 50 to 90). The BTF-DSS recommends an "Appropriate" instructional level for these questions (indicated by the numerical value 1 or 2), suggesting that they align well with students' abilities and knowledge levels. Questions Q2 and Q7 have moderate difficulty levels (ranging from 40 to 60), moderate student performances (ranging from 60 to 70), moderate time to answer (ranging from 20 to 40 seconds), and moderate prior knowledge (ranging from 50 to 60). The BTF-DSS also suggests an "Appropriate" instructional level for these questions (indicated by the numerical value 1), indicating that they are suitable for students with average abilities and knowledge. Question Q5 has a low difficulty level (20), low student performance (30), short time to answer (15 seconds), and low prior knowledge (40). The BTF-DSS recommends a "Too Easy" instructional level for this question (indicated by the numerical value 0), suggesting that it might be too simplistic even for students with limited knowledge. Question Q3 has a high difficulty level (90), low student performance (20), long time to answer (70 seconds), and low prior knowledge (30). The BTF-DSS suggests a "Challenging" instructional level for this question (indicated by the numerical value 0), recognizing that it could be difficult for students with lower performance and limited prior knowledge shown in figure 5. Table 5 demonstrates how the BTF-DSS can effectively assess and recommend appropriate instructional levels for educational questions based on multiple parameters, including difficulty level, student performance, time to answer, and prior knowledge. By considering these factors simultaneously, the BTF-DSS assists educators in designing tailored learning experiences that match individual students' abilities and knowledge levels.

## IV. CONCLUSION

The Bloom's Taxonomy Fuzzy Decision Support System (BTF-DSS) presented in this paper has demonstrated its potential to enhance the Oral English Teaching method from the perspective of the History and Pedagogy of Mathematics (HPM). By drawing parallels from the historical development and pedagogical approaches in mathematics education, the BTF-DSS leverages fuzzy logic and multiple parameters to recommend appropriate instructional levels for educational questions related to Oral English Teaching. Through the application of fuzzy logic, the system effectively handles uncertainty and vagueness in the input data, providing contextually relevant and personalized recommendations. The results from the BTF-DSS indicate that it can accurately assess the difficulty levels of questions and students' performance, while also considering factors such as time to answer and prior knowledge. The system's instructional level recommendations empower educators to create tailored learning experiences that cater to individual students' abilities, knowledge levels, and response times through Oral English teaching. By offering appropriate challenges and avoiding excessive difficulties, the BTF-DSS fosters an optimal learning environment, improving students' comprehension and engagement in the English language. Moreover, the use of fuzzy logic in the BTF-DSS aligns well with the interdisciplinary approach, allowing educators to explore the boundaries between different subjects, such as mathematics and language learning. The fusion of HPM principles and decision support systems in the Oral English Teaching context has the potential to enrich pedagogical practices and promote a deeper understanding of cognitive processes in language learning. While this study has showcased the promising outcomes of the BTF-DSS, further research and practical implementations are encouraged. Future endeavors should focus on validating the system with real-world data and expanding its scope to accommodate other language learning aspects. Additionally, investigating the long-term effects of employing the BTF-DSS on student outcomes and motivation would provide valuable insights for the continuous improvement of language teaching methods. It is concluded that the BTF-DSS offers a valuable contribution to the field of English language teaching oral manner by providing a robust, adaptable, and interdisciplinary approach that enhances instructional decision-making. With its ability to accommodate various parameters and leverage fuzzy logic, the BTF-DSS has the potential to revolutionize language education, enriching the learning experiences of students and empowering educators to nurture a new generation of proficient and confident English language learners.

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