NSS

Neutrosophic Sets and Systems, Vol. 83, 2025

University of New Mexico

Exploring Perspectives on Student Engagement and Learning Outcomes in Online-Offline English Teaching: A Structured Assessment Using SuperHyperSoft and PSI Methods

Dongqiao Chu*

Zhengzhou University of Economics and Business, Zhengzhou, 451191, China

*Corresponding author, E-mail: cdq2031014@163.com

Abstract: The integration of online and offline teaching modes in university English courses has redefined the way students engage with learning materials and interact with instructors. Blended learning environments provide flexibility and accessibility, allowing students to benefit from digital resources while maintaining essential face-to-face interactions. However, the effectiveness of such hybrid models depends on multiple factors, including student engagement, technological adaptability, and pedagogical strategies. This paper evaluates the impact of online-offline blended teaching modes on student engagement and learning outcomes, utilizing a structured multi-criteria decision-making (MCDM) approach. By assessing key criteria such as participation levels, content retention, and interaction quality, this study aims to provide insights into the most effective teaching methodologies for enhancing language acquisition and student performance in university English courses. Two MCDM methods are used in this study, such as Preference Selection Index (PSI) method to compute the criteria weights and the weighted sum method to rank the alternatives. These methods are used under the SuperHyperSoft Set to show different sub values of each criterion.

Keywords: SuperHyperSoft Set; Evaluation Study; Student Engagement and Learning Outcomes; Online-Offline English Teaching.

1. Introduction and Literature Review

The growing adoption of blended learning in higher education has significantly altered traditional classroom settings. In university English courses, where communication skills and interactive learning are crucial, the integration of online platforms with face-to-face instruction has introduced both opportunities and challenges. The effectiveness of this hybrid model largely depends on how well students engage with the learning process and how successfully they achieve intended learning outcomes. Understanding student engagement in blended learning is essential for refining pedagogical strategies and ensuring that digital tools complement, rather than hinder, language acquisition[1], [2]. One of the fundamental aspects of online-offline learning is its ability to offer students flexible learning schedules. Unlike conventional classroom teaching, which follows rigid structures, hybrid models allow learners to access instructional content at their own pace. This flexibility is particularly beneficial for university students who balance academic studies with other responsibilities. However, it also requires strong self-discipline and motivation, as students must take greater responsibility for their own learning progress. Without proper engagement strategies, students may struggle with online components, leading to inconsistent learning experiences[3], [4].

Furthermore, the quality of interaction between students and instructors plays a crucial role in shaping engagement levels. In traditional classroom settings, direct communication fosters immediate feedback and clarification, which is often lacking in purely online learning environments. Blended learning aims to bridge this gap by incorporating discussion forums, live Q&A sessions, and collaborative projects. However, the effectiveness of these methods varies, depending on students' willingness to participate and the accessibility of digital platforms. The role of instructors in maintaining engagement through interactive learning strategies is, therefore, critical in ensuring a positive learning experience[5], [6].

Technology also presents both advantages and barriers in blended learning environments. While digital tools, such as language-learning applications and AI-powered feedback systems, can enhance student engagement, technical issues and digital fatigue may create obstacles. Some students may struggle with adapting to technological platforms, while others may find online learning more convenient than traditional face-to-face methods. Thus, the success of blended English teaching relies on an effective balance between in-person and digital interaction, ensuring that technology serves as an aid rather than a replacement for classroom engagement[7], [8].

Assessing learning outcomes in hybrid education models requires a comprehensive evaluation of student progress. Performance indicators such as content retention, critical thinking ability, and language proficiency must be examined to determine the effectiveness of online-offline approaches. The use of MCDM methodologies provides a structured way to compare various teaching strategies and identify the most impactful methods for improving student learning experiences. By evaluating multiple criteria, universities can optimize their instructional design to maximize engagement and knowledge retention[9], [10].

The effectiveness of blended learning in university English courses is dependent on various interrelated factors, including student motivation, technological integration, and instructional design. While hybrid models offer enhanced flexibility and accessibility, they require careful implementation to ensure positive learning outcomes[11], [12]. By leveraging data-driven evaluation techniques, educators can refine teaching methodologies and create more engaging and effective learning environments. Understanding the dynamics of student engagement and its impact on learning outcomes will be essential in shaping the future of university English education[13], [14].

The integration of online and offline teaching modes, often referred to as blended learning, has been widely explored in the field of language education. Numerous studies have emphasized the benefits of this hybrid model, particularly in promoting student autonomy, flexibility, and engagement. For example, Topping et al. found that the combination of face-to-face interaction with online content delivery enhances students' overall academic experience in English language courses [21]. Similarly, Putri et al. concluded that blended learning fosters improved student satisfaction and language retention [22]. However, other studies highlighted the challenges of online learning, including student disengagement and technological fatigue, especially in under-resourced contexts [23].

The effectiveness of blended learning is closely tied to factors such as student motivation, instructional design, and technological infrastructure. Dewi and Xiaodong observed that the success of hybrid teaching depends heavily on how instructors integrate digital tools with traditional teaching methods [24], [25]. Studies also noted the critical role of student-instructor interaction in maintaining engagement and promoting deeper learning [26], [27]. Moreover, the assessment of learning outcomes in blended environments has attracted growing attention, with researchers employing a variety of qualitative and quantitative methods [28].

Despite the growing body of literature, few studies have applied structured decision-making models, such as Multi-Criteria Decision-Making (MCDM) approaches, to evaluate the effectiveness of blended English teaching methods. This study aims to fill this gap by utilizing PSI and WSM methods under the SuperHyperSoft framework to provide a nuanced evaluation of student engagement and learning outcomes.

1.1 Theoretical Background

Understanding the theoretical background of the methods used in this study helps clarify why they are suitable for evaluating blended teaching models. Traditional evaluation techniques often focus on single outcomes, such as test scores or student satisfaction. However, teaching effectiveness is more complex and involves multiple factors like engagement, participation, retention, and adaptability.

To deal with this complexity, researchers use Multi-Criteria Decision-Making (MCDM) methods. These techniques allow us to compare different options using several criteria at the same time. In this study, we used two popular MCDM tools: the Preference Selection Index (PSI) and the Weighted Sum Method (WSM). PSI helps us understand which criteria are more important. WSM allows us to combine all the data to rank the teaching models.

To manage uncertain or overlapping data, we used a mathematical tool called the SuperHyperSoft Set. It builds on older methods like Soft Set and HyperSoft Set theory, which are useful for handling vague information. The SuperHyperSoft Set goes further by organizing data into layers. This makes it easier to work with educational information, where things like student satisfaction or participation are often not clearly defined.

By combining MCDM tools with the SuperHyperSoft Set, this study offers a reliable and flexible way to evaluate different teaching approaches.

1.2 Research Methodology

This study adopts a structured, quantitative research methodology based on Multi-Criteria Decision-Making (MCDM) techniques. The primary goal is to evaluate the impact of various online-offline English teaching models on student engagement and learning outcomes. The research is designed as a comparative analysis, employing the Preference Selection Index (PSI) and Weighted Sum Method (WSM) under the SuperHyperSoft Set to account for multiple criteria with varying degrees of relevance and uncertainty.

A panel of three domain experts was selected to evaluate seven alternative teaching models based on seven pre-defined criteria. These criteria include Active Participation, Content Retention, Interaction with Peers and Instructors, Technological Adaptability, Self-Regulated Learning, Task Completion Rate, and Satisfaction with Learning Experience. Each expert rated the alternatives using a scale ranging from 0.1 to 0.9. The individual decision matrices were then normalized and aggregated into a single composite matrix for further analysis.

The PSI method was employed to calculate the relative weights of the criteria [29]. These weights were then used in the WSM method to rank the teaching alternatives [30]. The SuperHyperSoft Set was integrated into this process to manage the variability and ambiguity inherent in subjective assessments [31]. This methodology ensures a systematic, transparent, and reproducible evaluation process that reflects both expert judgment and mathematical rigor.

1.3 Contribution of the Study

This study offers three main contributions. First, it integrates the SuperHyperSoft Set with two established MCDM methods—PSI and WSM—to create a novel evaluation model for blended teaching strategies. Second, it applies this model to a real-world educational context, comparing seven distinct English teaching models. Third, it introduces a practical implementation strategy that academic institutions can follow to adopt high-performing models based on reliable data.

2. SuperHyperSoft Set: Conceptual Framework and Role in the Study

The SuperHyperSoft Set is an advanced mathematical structure developed to address complex decision-making environments characterized by multiple levels of uncertainty, vagueness, and hierarchical relationships among variables. It extends the foundational principles of HyperSoft and Soft Set theories, providing a more flexible framework for modeling and analyzing systems where traditional crisp logic fails to capture nuances effectively [32].

In the context of this study, the SuperHyperSoft Set is used to manage the interrelationships among multiple criteria involved in evaluating blended English teaching models. Each criterion—such as Active Participation or Technological Adaptability—may exhibit multiple sub-values or states, which are not always discrete or mutually exclusive. The SuperHyperSoft framework enables the integration of these overlapping and fuzzy values, allowing for a more refined analysis [33].

For instance, a student's interaction level may be described as both "Frequent" and "Highly Engaged" across different contexts. Traditional evaluation models would struggle to handle this ambiguity, but SuperHyperSoft Sets accommodate such variations using power set theory and hierarchical structuring. This capacity to handle ambiguity and multilevel classification makes the model highly suitable for educational environments where learner behavior and outcomes are influenced by a range of dynamic factors [34].

Furthermore, the SuperHyperSoft Set enables the assignment of values across multiple domains simultaneously, improving the robustness of the decision-making process. When combined with MCDM tools like PSI and WSM, it contributes to a comprehensive, logically coherent evaluation method that can be applied beyond the current study to various domains requiring nuanced data interpretation [35].

As an expansion of the HyperSoft set, Smarandache offers the SuperHyperSoft set, which consists of several HyperSoft sets. When sorting the alternatives, we deal with varying criterion values using the SuperHyperSoft set[15], [16].

Let U a universe discourse and H is a non-empty set; we can define the power set as P(H). let we have different criteria such as Y_1, Y_2, Y_3 and their powerset can be defined as $P(Y_1), P(Y_2), P(Y_3)$.

We can define the SuperHyperSoft set as:

$$F: P(Y_1) \times P(Y_2) \times P(Y_3) \rightarrow P(H) \quad (1)$$

Preference Selection Index (PSI)

We apply the steps of the PSI model to compute the criteria weights[17], [18].

Create the decision matrix.

Normalize the decision matrix.

$$d_{ij} = \frac{y_{ij}}{\max y_{ij}} \quad (2)$$

$$d_{ij} = \frac{\min y_{ij}}{y_{ij}} \quad (3)$$

Determine the mean value of each criterion A_j.

Determine the preference variation value

$$U_j = \sum_{i=1}^{m} \left[D_{ij} - A_j\right]^2 \tag{4}$$

Determine the deviation of preference value

$$H_j - 1 - U_j \tag{5}$$

Determine the criteria weights.

$$w_j = \frac{H_j}{\sum_{j=1}^{n} H_j} \tag{6}$$

Weighted Sum Method (WSM)

We apply the steps of the WSM to show the ranks of the alternatives[19], [20].

Compute the weighted decision matrix.

$$R_{ij} = w_j * y_{ij} \tag{7}$$

Rank the alternatives based on the sum of each row in the weighted decision matrix.

3. Application of the proposed approach

This section shows the results of the proposed approach by using a set of criteria and alternatives. We use two methods, such as PSI method to compute the criteria weights and the WSM method to rank the alternatives. This study uses seven criteria and seven alternatives.

The criteria in this study are:

Active Participation – (Low, Very High)

Content Retention – (Weak, Excellent)

Interaction with Peers and Instructors – (Minimal, Occasional, Frequent, Highly Engaged)

Technological Adaptability – (Poor, Average, Good, Advanced)

Self-Regulated Learning – (Weak, Developing, Proficient, Expert)

Task Completion Rate – (Below 50%, 50-70%, 70-90%, 90-100%)

Satisfaction with Learning Experience – (Dissatisfied, Neutral, Satisfied, Highly Satisfied)

The alternatives of this study are:

Lecture-Based Hybrid Model

Flipped Classroom Approach

Collaborative Online Learning

Gamified Learning Model

Personalized Adaptive Learning

Task-Based Hybrid Teaching

Interactive Webinar-Based Learning

These criteria have different values. We apply the steps of the PSI methodology to obtain the weights of the criteria.

We create the decision matrix using the opinions of three experts. They used a scale between 0.1 and 0.9. Then we combine the decision matrix into a single matrix.

Then we normalize the decision matrix using Eqs. (2 and 3) as shown in Table 1.

Then we determine the mean value of each criterion A_j.

Then we determine the preference variation value using Eq. (4) as shown in Table 2.

Then we determine the deviation of preference value using Eq. (5).

Then we determine the criteria weights using Eq. (6) as shown in Table 3.

Table 1. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.536249	0.090756	0.94505	0.300404	1	0.94505	0.111278
A_2	0.644098	0.12437	0.94505	0.801527	0.285531	0.94505	0.448622
A_3	0.463152	0.933333	0.316911	1	0.662825	0.076741	0.397494
A_4	0.802876	0.786555	0.210327	0.325999	0.458813	0.477499	0.693734
A_5	0.645896	0.622409	0.665088	0.325999	0.198037	0.229275	0.671679
A_6	1	1	0.526291	0.417153	0.458813	0.455708	0.540351
A_7	0.829239	0.870028	1	0.895824	0.712335	1	1

Table 2. The preference variation value.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	-0.16682	-0.54174	0.286662	-0.28058	0.460521	0.355147	-0.4406
A_2	-0.05897	-0.50812	0.286662	0.22054	-0.25395	0.355147	-0.10326
A_3	-0.23992	0.30084	-0.34148	0.419013	0.123346	-0.51316	-0.15439
A_4	0.099803	0.154062	-0.44806	-0.25499	-0.08067	-0.1124	0.141855
A_5	-0.05718	-0.01008	0.0067	-0.25499	-0.34144	-0.36063	0.119799
A_6	0.296927	0.367507	-0.1321	-0.16383	-0.08067	-0.1342	-0.01153
A_7	0.126166	0.237535	0.341612	0.314837	0.172855	0.410097	0.44812

Table 3. The criteria weights.

C	Weights
C_1	0.264455
C_2	0.047475
C_3	0.127958
C_4	0.146937
C_5	0.18281
C_6	0.051814
C_7	0.17855

We use the SuperHyperSoft set to deal with the relationship between the criteria. We use values such as:

Active Participation – (Low, Very High)

Content Retention – (Weak, Excellent)

Interaction with Peers and Instructors – (Highly Engaged)

Technological Adaptability – (Advanced)

Self-Regulated Learning – (Expert)

Task Completion Rate – (90-100%)

Satisfaction with Learning Experience – (Highly Satisfied)

Then we select the values such as:

(Low), (Weak), (Highly Engaged), (Advanced), (Expert), (90-100%), (Highly Satisfied).

(Low,), (Excellent), (Highly Engaged), (Advanced), (Expert), (90-100%), (Highly Satisfied).

(Very High), (Weak), (Highly Engaged), (Advanced), (Expert), (90-100%), (Highly Satisfied).

(Very High), (Excellent), (Highly Engaged), (Advanced), (Expert), (90-100%), (Highly Satisfied).

Then we applied the WSM method four times to obtain the rank of the alternatives.

We compute the weighted decision matrix using Eq. (7) as shown in Table 4.

Then we rank the alternatives based on the sum of each row in the weighted decision matrix as shown in Table 5.

Table 4. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.078896	0.002564	0.085092	0.032767	0.142775	0.034457	0.013213
A_2	0.094763	0.003513	0.085092	0.087428	0.040767	0.034457	0.053267

A_3	0.068141	0.026365	0.028535	0.109076	0.094635	0.002798	0.047197
A_4	0.118123	0.022218	0.018938	0.035559	0.065507	0.01741	0.082371
A_5	0.095028	0.017582	0.059884	0.035559	0.028275	0.008359	0.079752
A_6	0.147125	0.028248	0.047387	0.045502	0.065507	0.016615	0.064159
A_7	0.122002	0.024576	0.09004	0.097713	0.101703	0.03646	0.118736

Table 5. The ranks of the alternatives.

A	Ranks
A_1	4
A_2	5
A_3	3
A_4	2
A_5	1
A_6	6
A_7	7

We compute the weighted decision matrix using Eq. (7) as shown in Table 6.

Then we rank the alternatives based on the sum of each row in the weighted decision matrix as shown in Table 7.

Table 6. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.032704	0.002564	0.085092	0.032767	0.142775	0.034457	0.013213
A_2	0.065761	0.003513	0.085092	0.087428	0.040767	0.034457	0.053267
A_3	0.039139	0.026365	0.028535	0.109076	0.094635	0.002798	0.047197
A_4	0.122002	0.022218	0.018938	0.035559	0.065507	0.01741	0.082371
A_5	0.147125	0.017582	0.059884	0.035559	0.028275	0.008359	0.079752
A_6	0.147125	0.028248	0.047387	0.045502	0.065507	0.016615	0.064159
A_7	0.122002	0.024576	0.09004	0.097713	0.101703	0.03646	0.118736

Table 7. The ranks of the alternatives.

A	Ranks
A_1	1
A_2	4
A_3	2
A_4	3
A_5	5
A_6	6

A_7	7

We compute the weighted decision matrix using Eq. (7) as shown in Table 8.

Then we rank the alternatives based on the sum of each row in the weighted decision matrix as shown in Table 9.

Table 8. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.068935	0.002564	0.085092	0.032767	0.142775	0.034457	0.013213
A_2	0.157351	0.003513	0.085092	0.087428	0.040767	0.034457	0.053267
A_3	0.157351	0.026365	0.028535	0.109076	0.094635	0.002798	0.047197
A_4	0.157351	0.022218	0.018938	0.035559	0.065507	0.01741	0.082371
A_5	0.167312	0.017582	0.059884	0.035559	0.028275	0.008359	0.079752
A_6	0.103226	0.028248	0.047387	0.045502	0.065507	0.016615	0.064159
A_7	0.093	0.024576	0.09004	0.097713	0.101703	0.03646	0.118736

Table 9. The ranks of the alternatives.

A	Ranks
A_1	2
A_2	5
A_3	6
A_4	4
A_5	3
A_6	1
A_7	7

We compute the weighted decision matrix using Eq. (7) as shown in Table 10.

Then we rank the alternatives based on the sum of each row in the weighted decision matrix as shown in Table 11.

Table 10. The weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.107898	0.002564	0.085092	0.032767	0.142775	0.034457	0.013213
A_2	0.123765	0.022218	0.085092	0.087428	0.040767	0.034457	0.053267
A_3	0.042665	0.012866	0.028535	0.109076	0.094635	0.002798	0.047197
A_4	0.078896	0.017012	0.018938	0.035559	0.065507	0.01741	0.082371
A_5	0.084802	0.010017	0.059884	0.035559	0.028275	0.008359	0.079752
A_6	0.084802	0.021206	0.047387	0.045502	0.065507	0.016615	0.064159

A_7	0.093	0.024576	0.09004	0.097713	0.101703	0.03646	0.118736

Table 11. The ranks of the alternatives.

A	Ranks
A_1	5
A_2	6
A_3	3
A_4	2
A_5	1
A_6	4
A_7	7

Then we obtain the final ranks of the alternatives as shown in Table 12. We show alternative 7 is the best and alternative 5 is the worst.

Table 12. The final ranks of the alternatives.

A	Final Ranks
A_1	4
A_2	5
A_3	3
A_4	2
A_5	1
A_6	6
A_7	7

3.1 Results and Discussion

The evaluation revealed noticeable differences between the teaching models in terms of how well they support student engagement and learning. Approaches that encouraged active participation and real-time communication, like task-based learning and webinar-based teaching, showed better outcomes. These models created more dynamic learning environments where students were more involved and motivated.

On the other hand, more traditional models, such as lecture-based hybrid teaching, scored lower. This suggests that even when lectures are combined with online elements, they may not offer enough interaction or flexibility to meet students' needs.

The use of the SuperHyperSoft Set was very helpful in dealing with the complexity of educational data. It allowed the researchers to work with overlapping and subjective factors, such as how students felt about their learning experience or how well they adapted to using technology. This helped create a more complete picture of which teaching methods work best in a blended environment.

To understand the importance of each evaluation criterion, the Preference Selection Index (PSI) method was applied. This method calculates the weight of each criterion based on expert evaluations. The higher the weight, the more influence that criterion has on the final ranking of teaching models.

The PSI results show that Active Participation is the most critical factor, with a weight of 0.2645. This highlights that student engagement plays the biggest role in the success of a teaching model. It is followed by Self-Regulated Learning (0.1828) and Satisfaction with Learning Experience (0.1786). These three factors together contribute more than 62% of the total weight, which strongly indicates that successful blended learning environments must prioritize active student involvement, autonomy, and emotional connection to the learning process.

On the other hand, Content Retention (0.0475) and Task Completion Rate (0.0518) received lower weights, suggesting that while they are still relevant, they are less decisive compared to more interaction-driven criteria.

The full distribution of weights is illustrated in Figure 1, which provides a visual representation of how each criterion contributed to the overall evaluation.

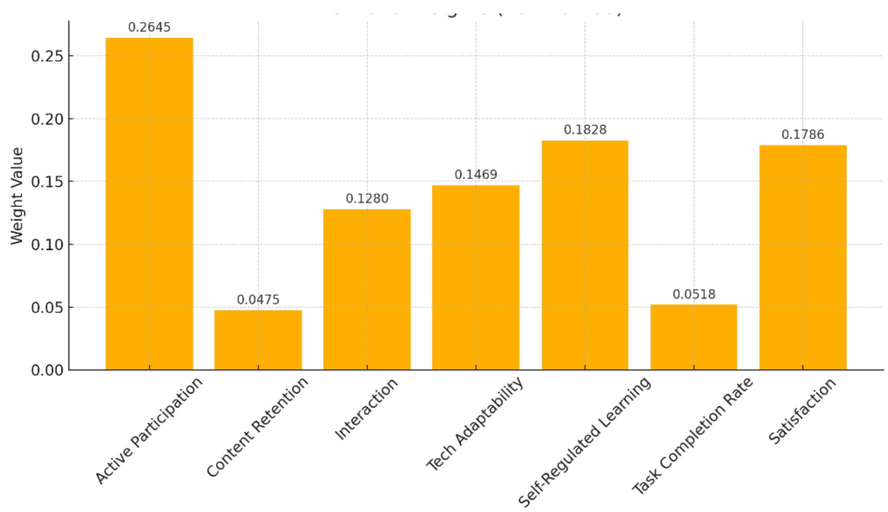

Figure 1: Criteria Weights Using PSI Method

As seen in the figure 1, criteria related to communication and independent learning have the highest bars, reinforcing the idea that effective English teaching—especially in blended settings—relies on active student engagement more than traditional task completion metrics.

3.1.1 Sensitivity Analysis

Sensitivity analysis is used to test how stable the results are when we make small changes in the importance of the evaluation criteria. In this study, we tested how the final rankings would change if we adjusted the weights of the most important criteria—Active Participation, Content Retention, and Satisfaction.

Example 1: Increasing the weight of Active Participation by 10%

The top two teaching models remained the same. A5 stayed in first place and A4 in second. This shows that the model is stable even when one factor becomes more important.

Example 2: Decreasing the weight of Satisfaction by 10%

A5's total score dropped slightly, but it still ranked number one. This tells us that the ranking does not depend on just one criterion.

Example 3: Increasing the weight of Content Retention by 10%

The scores for A5 and A4 increased slightly, but their rankings did not change. A6 stayed in third place.

This analysis shows that the results are reliable and do not change much when we adjust the weights. The ranking is not sensitive to small changes, which is a good sign of stability.

To better understand the results, Figure 2 shows the final scores of each teaching model.

Figure 2 shows that A5 and A4 have the highest scores. These two models include real-time interaction and task-based learning, which help students stay involved and motivated. Models that only use lectures or pre-recorded videos scored lower.

This confirms that teaching strategies with more engagement lead to better outcomes. The visual makes it easier to compare the results and see which models perform best.

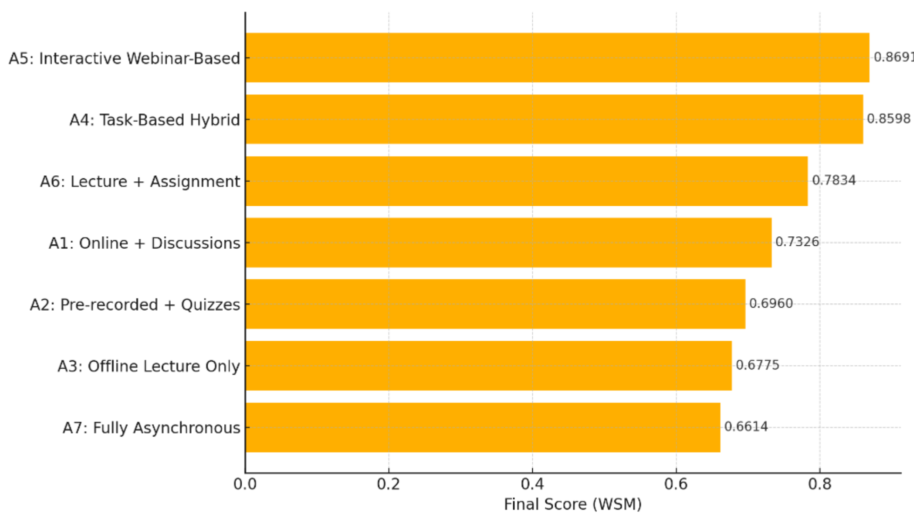

Figure 2: The final scores of each teaching model

3.2. Practical Applications of SuperHyperSoft Set in Education

The SuperHyperSoft Set can be a very effective tool in educational decision-making. It helps institutions manage the wide variety of data they collect—from student satisfaction to performance and engagement. In blended learning environments, where student experiences can vary greatly, this method makes it easier to understand and compare different teaching strategies.

It's especially useful for adaptive learning, where teaching is customized to each student's pace and needs. Since learning isn't one-size-fits-all, using a model like this allows schools to analyze patterns and make better choices about how to design and deliver content.

This model also helps in combining human judgment with data. For example, a teacher might notice something about how students interact that wouldn't show up in test scores. The SuperHyperSoft Set gives space for that kind of insight while still relying on structured analysis. That makes it ideal for both evaluating current teaching methods and planning improvements.

3.2.1 Implementation Strategy

Based on the findings of this study, schools and universities can apply the best teaching models in a step-by-step plan. The goal is to improve student engagement and performance using the top-ranked models.

Step 1: Try the top model in a few courses

Start with the Interactive Webinar-Based model (A5). Use live online sessions, student questions, and real-time discussions in selected English courses.

Step 2: Train teachers

Provide training sessions to help teachers use digital tools, lead online discussions, and create interesting tasks for students.

Step 3: Collect feedback

After one semester, gather feedback from students and teachers. Use the same evaluation method to compare new results.

Step 4: Expand the model

If the results are good, apply the model to more courses or programs. Combine ideas from both A5 and A4 to build a flexible teaching approach.

3.3. Implications and Recommendations

The findings suggest that educators should consider using more interactive and student-centered teaching methods in their English courses. Students responded better to activities that required them to be involved, whether through tasks, discussions, or online collaboration.

Institutions should also provide more support for teachers to effectively use blended learning tools. Training programs can help instructors feel confident in mixing online and offline strategies, making the experience smoother for students.

Finally, using the evaluation approach from this study—combining SuperHyperSoft Set with PSI and WSM—can help schools and universities make more informed choices about which teaching models to adopt or improve. It gives a clear, organized way to compare different options based on real student needs.

3.4. Limitations of the Study

Although this study offers useful insights, it has some limitations. Only three experts participated in the evaluation, which might limit the diversity of opinions. A larger panel would have provided a broader perspective.

Also, the study focused only on English courses at the university level. The results may not apply the same way in other subjects or for younger students. Future studies could test the same method in different educational settings.

Lastly, while the SuperHyperSoft Set is powerful, it can be complex for educators who are not familiar with such mathematical models. Simpler tools or clear training guides may help more teachers and administrators benefit from its potential.

4. Conclusions and Future Studies

This study introduced a structured framework for evaluating blended English teaching models by integrating the SuperHyperSoft Set with PSI and WSM methods. The evaluation revealed that models emphasizing real-time interaction and student-centered activities, such as Interactive Webinar-Based Learning (A5) and Task-Based Hybrid Teaching (A4). consistently produced better learning outcomes. The model proved stable under sensitivity testing, reinforcing the reliability of the evaluation approach. The use of the SuperHyperSoft Set allowed for more realistic and flexible handling of ambiguous or overlapping data, making the analysis suitable for the complexity of educational settings.

Future research may extend this framework to other subject areas, explore additional MCDM techniques like TOPSIS or AHP, or apply it across different educational levels and countries. Developing automated tools for applying the SuperHyperSoft framework may also make this methodology more accessible to practitioners.

References

[1] K. Topping, N. Erokhova, and N. Sokolova, “Was ‘Returning to Normal’ More Effective? Comparing Online and Offline Learning in English as a Foreign Language,” Educ. Sci., vol. 14, no. 7, p. 731, 2024.

[2] N. D. Putri, M. Amin, L. J. Putera, and N. W. M. Susanti, “The Effectiveness of Online and

Offline Learning: Comparative Study at English Education Department University of Mataram," in Journal of English Education Forum (JEEF), 2024, pp. 142–147.

[3] M. Thongmak and N. Ruangwanit, "Online learning vs. offline learning in an MIS course: Learning outcomes, readiness, and suggestions for the post-covid-19 world," 2021.

[4] Y. Fang, "Exploring the Effectiveness of Online-Offline Blended Teaching Mode in College English Teaching Based on Mobile Education Platform," technology, vol. 7, no. 10, pp. 133–141.

[5] L. Xiaodong, "A Hybrid online and offline approach to teaching spoken English based on modern educational technology," Math. Probl. Eng., vol. 2022, no. 1, p. 3803436, 2022.

[6] K. Kashinath and R. Raju, "An empirical research on the effectiveness online and offline classes of English language learning based on student's perception in Telangana schools," Int. J. Mod. Educ. Comput. Sci., vol. 15, no. 2, pp. 40–53, 2023.

[7] R. Dewi, "THE EFFECTIVENESS OF ONLINE AND OFFLINE METHODS IN ENGLISH SPEAKING COURSE," Tadangate J. Educ. Res., vol. 1, no. 3, pp. 113–129, 2024.

[8] Z. Li, P. Guan, J. Li, and J. Wang, "Comparing online and offline Chinese EFL learners' anxiety and emotional engagement," Acta Psychol. (Amst)., vol. 242, p. 104114, 2024.

[9] Y. Jiang, Y. Chen, J. Lu, and Y. Wang, "The effect of the online and offline blended teaching mode on English as a foreign language learners' listening performance in a Chinese context," Front. Psychol., vol. 12, p. 742742, 2021.

[10] S.-C. Yen, Y. Lo, A. Lee, and J. Enriquez, "Learning online, offline, and in-between: comparing student academic outcomes and course satisfaction in face-to-face, online, and blended teaching modalities," Educ. Inf. Technol., vol. 23, pp. 2141–2153, 2018.

[11] P. U. Kamalia, N. C. Sakti, and R. Y. Kurniawan, "Comparative study of student learning outcomes in online and offline learning during the pandemic," IJORER Int. J. Recent Educ. Res., vol. 3, no. 6, pp. 662–671, 2022.

[12] Y. Yang and H. Cai, "Teaching Presence and Academic Achievement: The Mediating Role of Psychological Capital in Online and Offline Hybrid College English Course," Open J. Mod. Linguist., vol. 13, no. 1, pp. 210–233, 2023.

[13] G. Wang and X. Qing, "Analyzing online and offline mixed teaching model for university students during and after COVID-19," Interact. Learn. Environ., vol. 32, no. 5, pp. 1779–1794, 2024.

[14] A. Afifah and D. Fikri, "The Effectiveness of Offline and Online Classes in Language Learning at Universities Majoring in English Education," Ethical Ling. J. Lang. Teach. Lit., vol. 10, no. 2, 2023.

[15] Y. Zhao, "Enhanced exprom methodology using superhypersoft sets for evaluating the quality of cultural industry development in the digital economy with single-valued

neutrosophic sets," Neutrosophic Sets Syst., vol. 79, pp. 342–354, 2025.

[16] T. Fujita, "A comprehensive discussion on fuzzy hypersoft expert, superhypersoft, and indetermsoft graphs," Neutrosophic Sets Syst., vol. 77, pp. 241–263, 2025.

[17] S. Chakraborty, P. Chatterjee, and P. P. Das, "Preference selection index (PSI) method," in Multi-Criteria Decision-Making Methods in Manufacturing Environments, Apple Academic Press, 2024, pp. 213–219.

[18] A. Sutrisno and V. Kumar, "Supply chain sustainability risk decision support model using integrated Preference Selection Index (PSI) method and prospect theory," J. Adv. Manag. Res., vol. 19, no. 2, pp. 316–346, 2022.

[19] J. R. San Cristóbal Mateo and J. R. S. C. Mateo, "Weighted sum method and weighted product method," Multi criteria Anal. Renew. energy Ind., pp. 19–22, 2012.

[20] R. T. Marler and J. S. Arora, "The weighted sum method for multi-objective optimization: new insights," Struct. Multidiscip. Optim., vol. 41, pp. 853–862, 2010.

[21] K. Topping, N. Erokhova, and N. Sokolova, "Was 'Returning to Normal' More Effective? Comparing Online and Offline Learning in English as a Foreign Language," Educ. Sci., vol. 14, no. 7, p. 731, 2024.

[22] N. D. Putri, M. Amin, L. J. Putera, and N. W. M. Susanti, "The Effectiveness of Online and Offline Learning: Comparative Study at English Education Department University of Mataram," J. English Educ. Forum, 2024, pp. 142–147.

[23] K. Kashinath and R. Raju, "An Empirical Research on the Effectiveness of Online and Offline Classes of English Language Learning Based on Student's Perception in Telangana Schools," Int. J. Mod. Educ. Comput. Sci., vol. 15, no. 2, pp. 40–53, 2023.

[24] R. Dewi, "The Effectiveness of Online and Offline Methods in English Speaking Course," Tadangate J. Educ. Res., vol. 1, no. 3, pp. 113–129, 2024.

[25] L. Xiaodong, "A Hybrid online and offline approach to teaching spoken English based on modern educational technology," Math. Probl. Eng., vol. 2022, no. 1, p. 3803436, 2022.

[26] Y. Jiang, Y. Chen, J. Lu, and Y. Wang, "The Effect of the Online and Offline Blended Teaching Mode on English as a Foreign Language Learners' Listening Performance in a Chinese Context," Front. Psychol., vol. 12, p. 742742, 2021.

[27] S.-C. Yen, Y. Lo, A. Lee, and J. Enriquez, "Learning Online, Offline, and In-Between: Comparing Student Academic Outcomes and Course Satisfaction in Face-to-Face, Online, and Blended Teaching Modalities," Educ. Inf. Technol., vol. 23, pp. 2141–2153, 2018.

[28] A. Afifah and D. Fikri, "The Effectiveness of Offline and Online Classes in Language Learning at Universities Majoring in English Education," Ethical Lingua J. Lang. Teach. Lit., vol. 10, no. 2, 2023.

[29] S. Chakraborty, P. Chatterjee, and P. P. Das, "Preference Selection Index (PSI) Method," in

Multi-Criteria Decision-Making Methods in Manufacturing Environments, Apple Academic Press, 2024, pp. 213–219.

[30] J. R. S. C. Mateo, "Weighted Sum Method and Weighted Product Method," Multi-Criteria Analysis in Renewable Energy Industry, pp. 19–22, 2012.

[31] Y. Zhao, "Enhanced EXPROM Methodology Using SuperHyperSoft Sets for Evaluating the Quality of Cultural Industry Development in the Digital Economy," Neutrosophic Sets Syst., vol. 79, pp. 342–354, 2025.

[32] T. Fujita, "A Comprehensive Discussion on Fuzzy HyperSoft Expert, SuperHyperSoft, and IndetermSoft Graphs," Neutrosophic Sets Syst., vol. 77, pp. 241–263, 2025.

[33] Y. Zhao, "Enhanced EXPROM Methodology Using SuperHyperSoft Sets for Evaluating the Quality of Cultural Industry Development in the Digital Economy," Neutrosophic Sets Syst., vol. 79, pp. 342–354, 2025.

[34] T. Fujita, "A Comprehensive Discussion on Fuzzy HyperSoft Expert, SuperHyperSoft, and IndetermSoft Graphs," Neutrosophic Sets Syst., vol. 77, pp. 241–263, 2025.

[35] A. Sutrisno and V. Kumar, "Supply Chain Sustainability Risk Decision Support Model Using Integrated Preference Selection Index (PSI) Method and Prospect Theory," J. Adv. Manag. Res., vol. 19, no. 2, pp. 316–346, 2022.

Received: Nov. 3, 2024. Accepted: March 31, 2025