

RESEARCH ARTICLE

A VIKOR–Based Framework for High–Precision Language Translation Systems Using Fuzzy Logic and Deep Learning

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ABSTRACT: This research introduces a novel approach to improve machine translation systems by combining fusion fuzzy logic (FFL) with deep learning techniques. It addresses key translation challenges, focusing on factors such as word adaptability, comprehension, verification time, error location, and word usage efficiency. We propose a fusion-based precision translation approach (FPTA) that combines advanced fuzzy algorithms with deep learning to cope with the uncertainty and complexity of cross-language translation. By using the VIKOR multi-criteria decision-making approach, we conduct a systematic evaluation and comparison of four different translation models. Neural machine translation with latent feature encoders (NMT-LFE), source language sentence extraction with deep neural networks (SLSE-DNN), multimodal neural machine translation (MNMT), and the proposed FPTA. Through a detailed analysis of these models on five key performance metrics, we highlight the performance of our hybrid approach. The results show that NMT-LFE excels in word adaptability (98.45%) and SLSE-DNN in comprehension (87.23%), while the FPTA model provides balanced performance across various dimensions, especially in verification time (97.23%) and error handling (87.60%), making it suitable for applications requiring high accuracy and reliability. The weighted normalized decision matrix obtained from the VIKOR method highlights word adaptability as a key factor affecting translation quality (selectivity). Score: 0.95218), followed by comprehension (0.53037) and word usage efficiency (0.39787). These insights suggest that prioritizing adaptability in model training and optimization will improve future translation systems. The VIKOR method further strengthens the approach by providing a structured framework for model evaluation and decision-making under multiple conflicting criteria. This research has valuable implications for high-precision translation applications such as international business communications, medical documentation, legal translations, and cross-cultural knowledge sharing platforms, where accuracy and contextual relevance are essential.

Keywords: Fusion Fuzzy Logic (FFL), Deep Learning Translation, VIKOR Decision Method Precision Translation Approach, Neural Machine Translation.

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1. INTRODUCTION

Combining fuzzy logic systems with artificial neural networks (ANNs) enables the creation of intelligent and adaptive systems. ANNs learn by modifying the connections

between their layers, whereas fuzzy logic inference systems provide a computational framework based on fuzzy set theory, rule-based reasoning, and inference algorithms. This synergy of adaptability and reasoning creates what is called a "neuron-fuzzy" system. [1] One of the primary challenges in stress detection is to accurately classify image data based on facial expressions. This study presents a fusion fuzzy logic (FFL) method combined with deep learning to detect signs of depression from facial segments. The proposed model also uses a fuzzy algorithm enhanced with deep learning techniques to generate unordered fuzzy rules (FR), which

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allows for accurate and insightful interpretation of facial expressions associated with depression. [2] These factors lead to fuzzy data, which hinders accurate analysis, interpretation of results, and understanding of complex symptoms. To overcome this, fuzzy logic is combined with deep learning to create fuzzy deep learning, which effectively handles uncertain data and provides interpretable insights, representing a significant advance in Alzheimer's disease (AD) research. [3] Deep learning, also known as "image-based machine learning", has been recognized as a very useful approach in the field of medical imaging. Recently, deep learning techniques have made significant advances in skin lesion analysis. [4] Deep learning has proven to be highly effective across various applications, capable of addressing complex and challenging problems.

In this research, we introduce an innovative enhancement to deep learning: the fuzzy layer. [5] Deep learning in medical applications will improve efficiency, reduce manual efforts, and provide radiologists with critical insights that are invisible to the human eye, with greater accuracy than current methods. It automatically detects key features that can reveal even the most subtle signs in histopathology images. [6] This task is complicated by the nonlinearity, dynamic interactions, and interdependence of variables in renewable energy systems. The challenge is exacerbated when floating offshore wind farms face extreme weather and wave disturbances. To address this challenge, we propose a hybrid approach that combines fuzzy logic with deep learning. In this framework, deep learning algorithms analyse existing wind conditions and predict future wind patterns. [7] We introduce a fusion fuzzy logic (FFL) approach combined with deep learning to detect depression through facial expressions. Our model uses sophisticated fuzzy algorithms with deep learning to generate unordered fuzzy rules (FR), which provide accurate insights into the emotional states of individuals. This framework supports depression recognition (DR) from both still images and recorded video data. [8] Deep learning (DL) techniques, especially deep neural networks (DNNs), have become a robust framework for extracting task-specific features from large-scale datasets. These methods have demonstrated significant performance in diverse domains such as image and video analysis, audio description, natural language processing, economic forecasting, and robotics. [9] To overcome the challenges.

In relation to the source language, this study introduces a qualitative translation method based on fusion, which combines deep learning with fuzzy logic. This approach improves both the accuracy and efficiency of the translation process. Translation accuracy by reducing verification time, reducing error rates, and improving the selection of accurate vocabulary. [10] Deep learning has shown remarkable ability to generate accurate predictions from complex datasets. Convolution neural networks (CNNs) are particularly useful for tasks involving image classification. While recurrent neural networks (RNNs) have shown strong performance in applications such as caption generation and language translation. However, a significant drawback of these models

is their limited interpretability, as they typically do not provide insight into the reasoning behind their outputs. [11] This research explores the use of fuzzy deep learning models in dealing with uncertain medical data and related situations. Providing an in-depth study of their performance evaluation metrics. Notably, it offers several innovative contributions, including the introduction of four unique frameworks designed to effectively use fuzzy deep learning models in addressing uncertainty within medical datasets. [12] Deep learning networks have a wide range of modern applications and show exceptional performance. While their use in real-world problems is growing, the exact reasons for their performance are unclear. However, insights can be gained by studying the behaviour of the network through experimental analysis. [13] Deep learning has become a powerful AI technique for data-intensive tasks, allowing for automated feature extraction and highly accurate predictions. However, deep learning models are often criticized for their black-box nature and limited interpretability, which hinders their use in safety-critical environmental fields. In contrast, fuzzy logic systems excel at managing imprecise and ambiguous data through human-like reasoning, although they lack the autonomous learning capabilities of deep learning models. [14] Deep learning combined with fuzzy systems provides a highly efficient integrated solution for vehicle speed management and collision prevention. By applying fuzziness to the speed variable, a more refined approach to speed regulation is achieved. Recent research has used recurrent neural networks (RNNs) and various deep learning techniques to predict traffic patterns and study traffic flow frequency. [15]

2. VIKOR METHOD

The VIKOR method is designed to deal with problems in multi-criteria decision making (MCDM), especially in situations where criteria may conflict and there is no unified measurement standard. It works on the premise that compromise is an acceptable solution to resolve conflicts. By evaluating all predefined criteria, the method seeks to determine the alternative that most closely matches the best solution. Its main goal is to rank and select alternatives in situations with conflicting criteria. [16] The VIKOR method, widely recognized for its use in optimizing multiple criteria within complex systems, is designed to rank and select alternatives involving conflicting criteria and varying units of measurement. This approach determines a compromise ranking by assessing how closely each option matches the best solution. The concept of compromise in this context refers to a solution that is achieved through mutual concessions between competing criteria. [17] The VIKOR method is well suited for optimizing problems involving multiple responses because it takes into account the variation in quality losses associated with each response. It effectively combines both utility and regret measures within a single experimental estimate, enabling a balanced evaluation of alternatives. [18] Unlike the TOPSIS method, Vector

normalization can produce normalized values for each parameter that vary depending on the unit of measurement.

In contrast, the VIKOR method uses linear normalization, which ensures that the resulting normalized values remain constant regardless of the units used. [19] To address the identified challenges, we introduce a high-accuracy decision recommendation system (DRS). This system combines intuitive Fuzzy sets (IFSs), term frequency-inverse document frequency (TF-IDF), and the VIKOR method have been integrated with the multi-criteria group decision making method (MCGDM) under incomplete information conditions (Wang and Zhang, Men and Chen; Yu et al.). [20] The extended fuzzy VIKOR method is used to prioritize failure modes based on their overall risk factors. The result is a risk assessment approach that combines weights with the fuzzy VIKOR method to address the challenges faced in Failure Modes and Effects Analysis (FMEA). [21] The VIKOR method is a multi-criteria decision-making approach (Opricović) developed to solve problems with conflicting criteria. It provides a compromise solution that serves as a practical alternative, closely resembling the optimal solution. [22] General procedures for the HFL-VIKOR method are outlined, along with several numerical examples demonstrating its advantages and real-world applications. The paper concludes by discussing the advantages of the HFL-VIKOR method and proposing potential areas for future research. [23] The VIKOR method seeks to maximize the overall benefit to the majority and minimize the individual disadvantage to the opposing party. It uses multi-attribute ranking indices to assess the closeness of each alternative to the optimal solution. [24] The modified VIKOR method helps to rank alternatives in three situations: alternatives with shared criteria, alternatives without common criteria, and alternatives with shared and unique criteria.

This paper includes numerical examples and a case study to show the performance of the proposed model and to evaluate the validity of this new approach. [25] This paper introduces an advanced probabilistic dual-hierarchical linguistic VIKOR method that improves on the traditional VIKOR approach. The advantages and practical applications of the proposed method are illustrated by its application to a real-world multi-criteria decision-making problem in the smart healthcare industry. [26] The decision support system outlined in this research uses the VIKOR method, which is designed to collect information from multiple attributes and criteria. The VIKOR method was chosen for its ability to effectively identify the most relevant criteria for determining decision outcomes that include a variety of attributes and criteria. [27] The VIKOR method, also known as the compromise ranking method, evaluates alternatives and identifies the solution that most closely matches the ideal, called the compromise solution. This study focuses on a limited number of alternatives for simplicity, but the model aims to evaluate a wide range of alternatives. The primary goal is to compare the characteristics of the alternatives and select the most suitable one. [28] This paper seeks to identify the optimal location that maximizes both profitability and

productivity for the company. Data from a popular label manufacturing company in Turkey is used to illustrate the facility location selection process. This study presents an analysis of facility location selection using AHP and VIKOR methods. [29] The VIKOR method uses a linear normalization technique to ensure that the normalized scores for each criterion are not affected by the units of measurement. Its aggregation function balances overall group satisfaction with satisfaction of individual criteria, while taking into accounts the relative importance of each criterion. [30]

3. MATERIAL AND METHODS

3.1. Alternative

3.1.1. Word Adaptability

Adaptability refers to the ability or willingness to adjust to different conditions. It is an essential trait in a constantly evolving work environment. International experience demonstrates adaptability and the ability to manage foreign languages. See: Adaptable.

3.1.2. Understand ability (%)

Comprehensibility refers to the quality of language or thought that is clear and easy to understand. Synonyms include comprehensibility.

3.1.3. Verification Time (s)

In computer science, time verification is the process of ensuring that tasks in real-time embedded systems complete their execution within designated deadlines.

3.1.4. Errors (Placement)

The most frequent machine translation errors include: mistranslation of proper nouns such as surnames and place names, mistranslation of incorrect siblings (false friends), and incorrect word order, which can change the intended meaning in some languages.

3.1.5. Word Usage (Sentence)

He was very particular about using English correctly. It is clear that the phrase originated in America before it became common in Britain. Some motor parts deteriorated due to continuous use. If your water consumption is low, switching to a meter may be beneficial.

3.2. Evolution

3.2.1. NMT-LFE

In neural machine translation (NMT), latent feature encoders (LFEs) are used to create a small, low-dimensional representation of the input text by capturing its key features. This encoded form is then sent to a decoder for translation. Often using techniques such as auto encoders, this approach improves the model's ability to understand the underlying structure and meaning of the text, leading to more accurate and fluent translations – especially useful for languages with limited data resources.

3.2.2. SLSE-DNN

To improve the accuracy of translation models by refining training content, deep neural networks (DNNs) use source language sentence extraction (SLSE). This method involves selecting relevant sentences from the source language to

enhance the dataset, resulting in a more reliable and accurate translation model. SLSE contributes to higher efficiency in machine translation by improving translation accuracy.

3.2.3. MNMT

Multimodal Neural Machine Translation (MNMT) translates a source language sentence using related images; however, these images often contain irrelevant or noisy information that does not match the source sentence.

3.2.4. FPTA

Fusion-based Precision Translation Approach (FPTA) is an on-demand translation technique that emphasizes ensuring the accuracy of translated words. It combines deep learning with a fuzzy decision algorithm to improve the accuracy and precision of long-distance translations.

Table 1. Fuzzy logic system deep learning and applications

	Fuzzy logic system deep learning and applications			
	NMT-LFE	SLSE-DNN	MNMT	FPTA
Word Adaptability	98.45	78.23	45.23	45.23
Understand ability (%)	67.23	87.23	65.55	87.23
Verification Time (s)	78.12	42.00	70.00	97.23
Errors (Placement)	20.22	76.23	78.00	87.60
Word Usage (/Sentence)	65.12	80.23	98.23	98.23

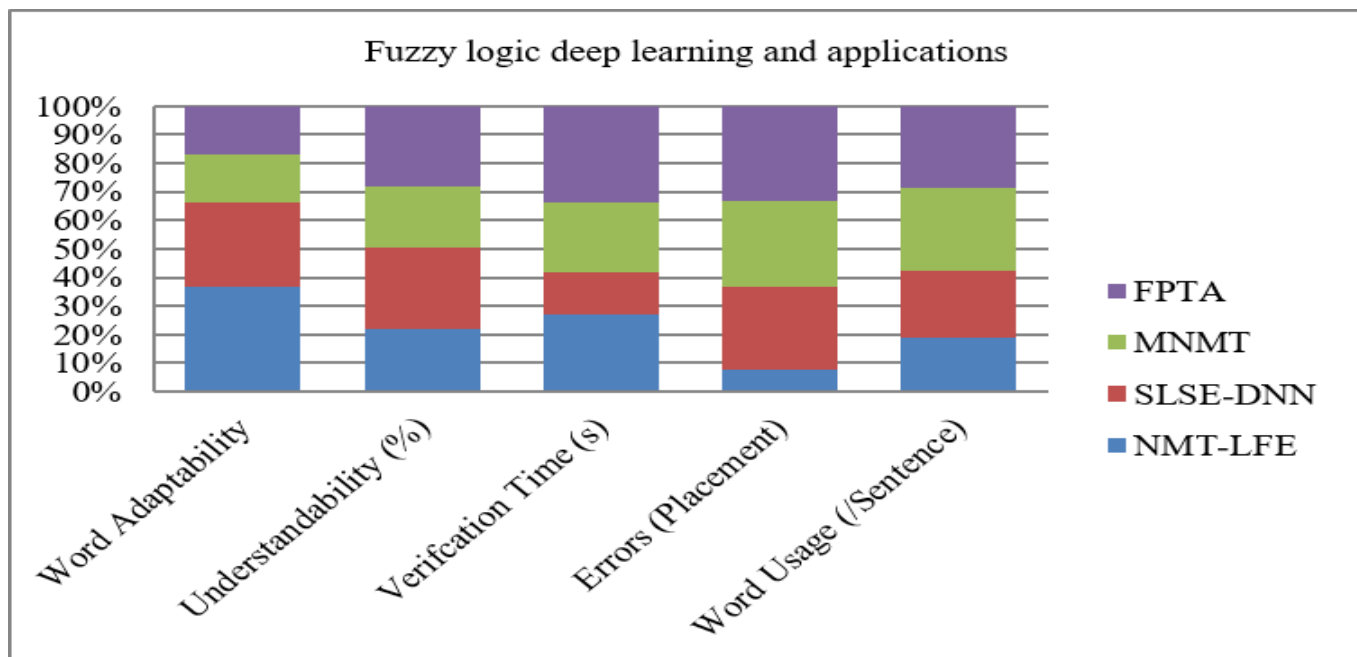


Fig. 1. Fuzzy logic system deep learning and applications.

Table 2. Performance value

	Performance value			
Word Adaptability	1.00000	0.89682	1.00000	1.00000
Understand ability (%)	0.68288	1.00000	0.69001	0.51851
Verifications Time (s)	0.79350	0.48149	0.64614	0.46519
Errors (Placement)	0.20538	0.87390	0.57987	0.51632
Word Usage (/Sentence)	0.66145	0.91975	0.46045	0.46045

4. RESULT AND DISCUSSION

Table 1 shows the interaction between the VIKOR method, fuzzy logic systems, and deep learning techniques. Their integration enhances decision-making by effectively managing uncertainty and imprecision. The combination of these advanced computational approaches benefits a range of applications, such as smart technologies, autonomous vehicles, and medical diagnostics, by offering greater accuracy and flexibility.

Figure 1 shows It demonstrates the interoperability of fuzzy logic systems, deep learning, and the VIKOR method on different models using a given dataset. Models such as NMT-LFE and SLSE-DNN show strong performance in word adaptation and understanding. The integration improves the speed of verification, reduces displacement errors, and increases the word usage efficiency in practical applications.

Table 2 shows the performance metrics of various models evaluated with the VIKOR method, emphasizing their applicability to fuzzy logic and deep learning. SLSE-DNN demonstrates robust results in understanding and word usage, while other models excel in word addictiveness. This comparison helps identify models that are more suitable for intelligent language-based applications. Table 3 shows the weight distribution used in the VIKOR method to facilitate interoperability between fuzzy logic systems and deep learning models. Each criterion, including word adaptability, comprehension, verification time, errors, and word usage, is given an equal weight of 0.45, ensuring balanced importance in Processes that involve making decisions based on multiple criteria or factors.

Table 4 provides a weighted normalized decision matrix using the VIKOR method, improving its integration with fuzzy logic and deep learning frameworks. The team reflects the adjusted performance values of each model, using equal weights to ensure accurate and consistent evaluation.

Table 3. Weight

	Weight			
Word Adaptability	0.45	0.45	0.45	0.45
Understand ability (%)	0.45	0.45	0.45	0.45
Verifications Time (s)	0.45	0.45	0.45	0.45
Errors (Placement)	0.45	0.45	0.45	0.45
Word Usage (/Sentence)	0.45	0.45	0.45	0.45

This approach fosters more effective decision making in intelligent system applications, where advanced algorithms such as machine learning, artificial intelligence, and other computational models are used to solve complex problems and improve efficiency. Figure 2 shows the weighted normalized decision matrix in the VIKOR method includes normalized values for each criterion, with weights assigned according to their importance. This matrix is used to evaluate alternatives in multi-criteria decision making, taking into account the relative importance of each criterion, and to identify the alternative that most closely matches the best solution. It is designed to integrate effectively with fuzzy logic and deep learning models.

Table 4. Weighted normalized decision matrix

	Weighted normalized decision matrix			
Word Adaptability	1.00000	0.95218	1.00000	1.00000
Understand ability (%)	0.84228	1.00000	0.84622	0.74412
Verifications Time (s)	0.90115	0.71972	0.82158	0.70865
Errors (Placement)	0.49052	0.94115	0.78253	0.74270
Word Usage (/Sentence)	0.83028	0.96306	0.70539	0.70539

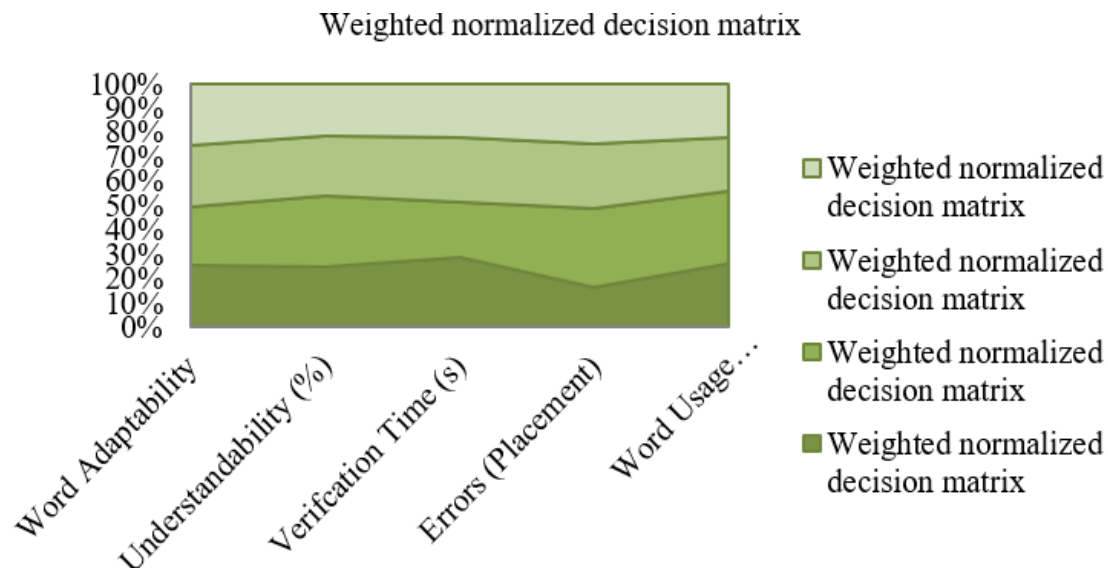


Fig. 2. Weighted normalized decision matrix.

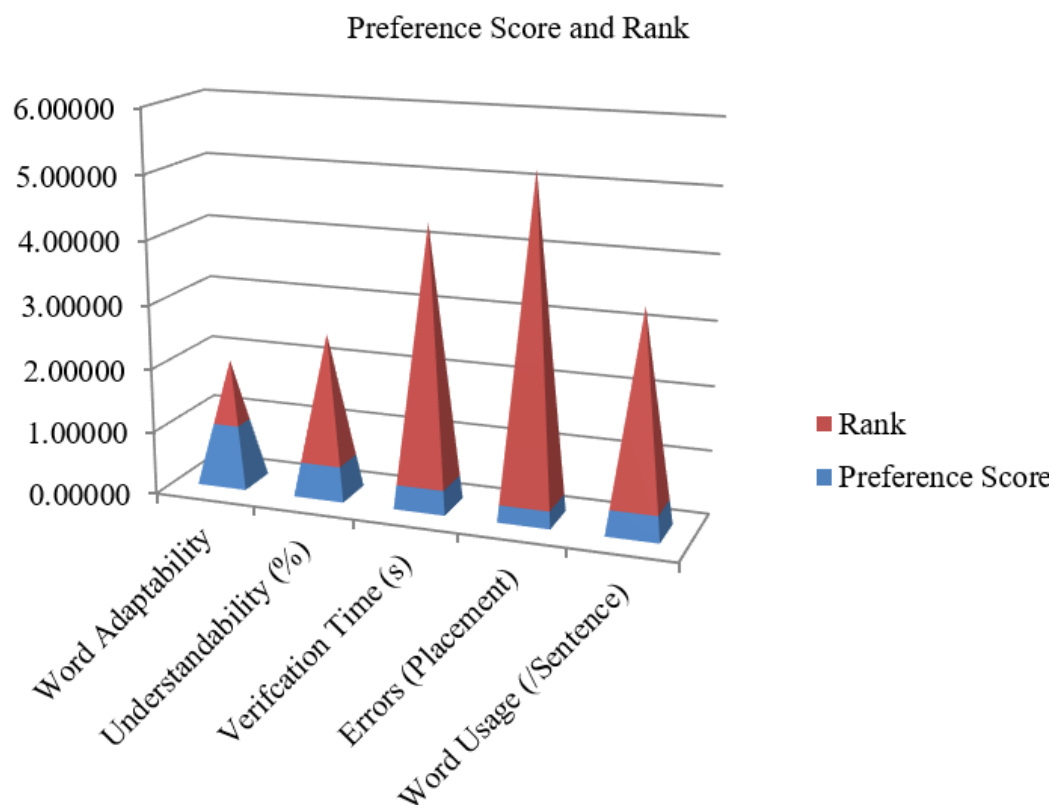


Fig. 3. Preference score and matrix.

Table 5. Preference score and rank.

Preference Score and Rank		
Word Adaptability	0.95218	1
Understand ability (%)	0.53037	2
Verifications Time (s)	0.37761	4
Errors (Placement)	0.26830	5
Word Usage (/Sentence)	0.39787	3

By using fixed weights, the matrix adjusts the performance values across criteria, promoting more efficient and balanced decision making. This organized approach improves comparative analysis, enabling more accurate and reliable decision making in adaptive intelligence systems and language processing tasks.

Table 5 displays a priority score and ranking matrix using the VIKOR method, ensuring interoperability with fuzzy logic and deep learning. Word adaptability ranks very high, underscoring its significant impact on model performance. The organized ranking system helps identify key performance priorities, improving decision-making in intelligent language-based systems. Figure 3 shows the preference scores and ranking matrix derived from the VIKOR method, highlighting its integration with fuzzy logic and deep learning approaches. Word adaptability ranks highest, followed by understand ability and word usage. This prioritization facilitates informed, data-driven decisions to improve the performance of intelligent language-based systems.

5. CONCLUSION

This study emphasizes the significant potential of integrating fusion fuzzy logic with deep learning. Techniques to improve machine translation systems. Through an in-depth evaluation using the VIKOR multi-criteria decision-making method, we identified key performance factors and established a framework for comparing translation models based on multiple conflicting criteria. Our analysis of four translation models – NMT-LFE, SLSE-DNN, MNMT, and the proposed FPTA – provided valuable insights into their strengths and limitations. The NMT-LFE model excelled in word addictiveness (98.45%), while the SLSE-DNN excelled in comprehension (87.23%). However, the FPTA model exhibited exceptional capabilities in verification time (97.23%) and error handling (87.60%), making it particularly suitable for applications requiring high accuracy and reliability. The weighted normalized decision matrix derived from the VIKOR method revealed word adaptability as the most important factor in translation quality, with a priority score of 0.95218, followed by comprehension (0.53037) and word usage ability (0.39787). These findings indicate that future development of translation systems should focus on prioritizing adaptability to linguistic variations during model training and optimization. The integration of the fuzzy layer improves the interpretability of deep learning models, addressing their “black box” nature while preserving their predictive power. Our research shows that the FPTA approach provides a balanced performance profile across various translation quality dimensions, making it particularly valuable for real-world applications where consistency across different translation features is more important than excelling in just one area. These findings are significant for high-precision translation applications such as international business communications, medical documents, legal translations, and cross-cultural knowledge sharing, where

both accuracy and contextual relevance are essential. Future research should aim to improve the integration of fuzzy logic and deep learning components. Explore adaptive weights for different translation contexts, and extend the model to support more language pairs. In addition, exploring the scalability of the FPTA approach for real-time translation applications offers an exciting path for further development.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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