Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 4313549, 11 pages
https://doi.org/10.1155/2022/4313549

Research Article

Establishment of a Fuzzy Comprehensive Evaluation Random Matrix Model for the Assessment of Foreign Language Translation Level in Universities

Li Xie and Jin Wu

Department of English, Hunan College of Foreign Studies, Changsha 410001, Hunan, China

Correspondence should be addressed to Jin Wu; wujin@huwai.edu.cn

Received 9 June 2022; Revised 27 July 2022; Accepted 2 August 2022; Published 27 August 2022

Academic Editor: Ning Cao

In this paper, the random matrix method of a fuzzy comprehensive evaluation is used to conduct in-depth research and analysis on the assessment of foreign language translation levels in universities, and the corresponding model is designed for the automatic assessment of translation levels in university education. The Hessian matrix of the second-order optimization method is used to analyze the geometric properties of the loss plane of the deep neural network, and it is proved that the Hessian matrix can be constructed as a sample covariance matrix, which is the classical Wishart matrix in the random matrix theory. Using the study on the asymptotic distribution properties of the Wishart matrix in random matrix theory, the Hessian matrix is analyzed and the limiting spectral distribution, the eigenvalue extreme value distribution, and the standard conditional number distribution of the matrix are given. And the scores are basically distributed above 240, but some indicators have relatively low scores, all below 120 points, so the indicators distributed above 240 points are selected as reserved indicators. The analysis considers that the evaluation of foreign language translation in learning in colleges and universities is itself very fuzzy and constructs an evaluation model based on the fuzzy comprehensive judgment method, which provides a research strategy for the future evaluation of foreign language translation in learning in colleges and universities. Finally, the evaluation system of foreign language translation in learning in colleges and universities is designed and implemented. It is feasible to apply the fuzzy comprehensive judgment to the comprehensive evaluation of college students, the combined judgment of multiple methods has higher reliability and stability, and its research conclusions have certain reference value in the specific education management practice. The value, objectivity, feasibility, and wide adaptability of the fuzzy comprehensive evaluation method are analyzed, and some references are expected to be provided for translation quality assessment research and translation practice.

1. Introduction

With the rapid development of globalization, the communication between speakers of different languages has increased dramatically, so high-quality translations are increasingly important. Translation quality assessment (TQA) is an important part of translation research, and a translation is not complete until it has been read and evaluated by readers and experts [1]. Therefore, in that sense, TQA is an essential part of translation research. However, for many years, due to the lack of a relatively objective and practical TQA model, translation researchers have mostly focused their attention on subjective criticism and error analysis of translations, with qualitative research as the focus, and TQA has not been given due attention and its role has not been fully played. However, in many cases, we need to evaluate translations quantitatively and objectively in a comprehensive manner. With the development of cross-discipline, fuzzy mathematics has been applied to translation research to evaluate translation quality objectively and quantitatively. Since fuzziness is an inherent property of all languages, and translation is an activity between different languages, fuzziness is inevitable.

With the advent of the DT era, the amount of data generated in many fields has increased dramatically, and it is difficult for humans to process the datasets with large scale and high complexity directly, so we need to use computer tools to classify and cluster these data moderately and effectively in advance. Pattern clustering includes supervised clustering and unsupervised clustering [2]. The purpose of supervised clustering is to find a mapping from the input data vector to a finite set of class labels, and such a mapping generally represented a numerical function containing several parameters to be determined, the estimated values of which can be determined using relevant learning algorithms [3]. In unsupervised clustering, on the other hand, no specific labeling of the data is required for classification or necessary data analysis. The mainstay of practical research and application is the objective function-based fuzzy clustering algorithm, which expresses the clustering problem as an optimization problem with constraints, and determines the partitioning of the dataset and the clustering results by finding a specific solution to the optimization problem. These algorithms are designed to be simple to apply and have good clustering effects, and the process is easy to program by using the mathematical theory of nonlinear programming to find the solution to the optimization problem.

In the process of implementing the evaluation of foreign language translation teaching in colleges and universities, according to the collected data, the evaluation results of experts, students, and teachers are calculated, respectively, then the evaluation results are obtained by comprehensive operation, and then the scoring method is used for experimental comparison [4]. Cultivate personal self-development so that they can play the greatest role in all aspects of life. The implementation results show that the evaluation method of foreign language translation teaching effectiveness in colleges and universities elaborated in this paper can well meet the needs of classroom teaching evaluation of English teachers. This paper adopts a quantitative evaluation method to evaluate foreign language translation teaching in colleges and universities, using methods including the scoring method and fuzzy comprehensive evaluation, in which the evaluation of the effectiveness of foreign language translation teaching in colleges and universities is a fuzzy comprehensive evaluation. The traditional comprehensive evaluation method has a wide range of use, but nowadays there is no single method that can solve all the problems that occur and is suitable for all kinds of teaching situations, and each method has its focus and area of existence. To solve specific problems in a particular field, it is necessary to integrate and analyze the system practically, and then reestablish an appropriate system with suitable algorithms to achieve it. Therefore, this paper proposes that this research has positive and far-reaching theoretical and practical implications for the improvement of teaching effectiveness in the field of education, as well as a reference value for other professional comprehensive evaluation methods.

2. Related Works

In the university foreign language translation in the learning environment, learners can use mobile or nonmobile terminal devices as learning platforms, and the system uses context-aware technology to detect information about the environment in which learners are located, personal learning goals, and learning processes, and provides learners with more adaptive personal support [5]. Compared with ubiquitous learning and mobile learning, foreign language translation in learning in colleges and universities can perceive the learner's situation in the real world, can provide personalized information and services more actively based on the context in which the learner is located, and can record the learner's information in the real world [6]. Thus, it seems that foreign language translation in learning in universities also belongs to the category of ubiquitous learning, which is a further step of mobile learning. Through situational awareness technology and wireless network technology, it can perceive the situation of learners in the real world, provide adaptive information and services more actively based about learners, and record the behavior of learners in the real world with information. Carrillo et al. used a spherical spin-glass model to explore the nonconvex loss function of a simple model of a fully connected feedforward neural network and found that the minimum critical value of the stochastic loss function lies within a narrow band definition and is bounded by a global minimum [7]. The study of the article is based on three assumptions: independence of variables, redundancy of network parameters, and homogeneity [8]. A large size decoupled network is analyzed, and the random loss function of the network exhibits a hierarchical structure at the lowest critical value, which is all contained in a narrow band, the lower line of which is the global minimum, while the number of local minima outside the band shows an exponentially decreasing relationship with the size of the network.

The difference between large and small networks highlighted, where lower quality local minima in small networks have a nonzero probability of being recovered, and the recovery of global minima becomes a more difficult task as the network size increases, which is why global minima often lead to overfitting in experiments [9]. Chen et al. performed extensive training and data processing, found that the Hessian matrix is degenerate at any moment, and deduced that the loss plane features are determined by both the network structure and the input dataset [10]. During the study of the spectrum of the Hessian matrix, it was found that increasing the number of network parameters scales most of the spectrum if the input data are fixed, and changing the input data affects larger values in the spectrum if the network dimension is fixed [11]. Yang et al. also proposed an automatic modulation classification method that incorporates a spectral correlation function and a neural network classifier, which is a neural network with a single continuous output [12]. Ozcanli et al. proposed a distributed processing-based decision system for classifying multiple radio signals, which consists of two main phases [13].

The fuzzy integrated evaluation method is used to analyze the evaluation indexes and transform the qualitative evaluation factors into quantitative evaluation factors, i.e., the total evaluation of things or objects subject to multiple factors, which makes the results clearer and the algorithm more reasonable and better solves the difficult problems. The main purpose is to explain and illustrate the relevant theories involved in the evaluation of the effectiveness of foreign language translation teaching in secondary schools under fuzzy comprehensive evaluation, including the principles of teaching evaluation, foreign language translation teaching evaluation, and fuzzy comprehensive evaluation method. The analysis and overview are mainly made from the practice environment, practice process, and comprehensive evaluation results, and the implementation steps and analysis process are introduced. Firstly, the weights are constructed with the values of the research, after which the relationship matrix is established from the evaluation indexes and the set of comments, and the relationship matrix is obtained by using the fuzzy evaluation method to calculate the weights of each index for experts, students, and teachers, respectively, and the evaluation values are calculated. And the results were subjected to classroom teaching experiments, and the experiments were compared by hierarchical analysis. To greatly demonstrate the advantages of the fuzzy overall assessment sample, this paper finally used the scoring method to complete the control of the experiment, and the results showed that the index weights derived from the model established in this paper could make the constructed judgment matrix more satisfactory.

3. Design of Foreign Language Translation-Level Evaluation in Higher Education

Evaluation is to determine the value of people or things, and we tend to make a subjective judgment only for the good or bad of people or things, which is one way of determining an evaluation [14]. Through the analysis and interpretation of the main components, the evaluation of the original indicators is achieved. The evaluation index system of this paper contains more than 30 evaluation parameters, so many evaluation indexes should choose a weighting method that can reduce the amount of calculation and the difficulty of the analysis process. In the activity, there is the problem of evaluation subject and evaluation object, to get the good and bad and as the final judgment result. In addition, the subject of evaluation is also the object of evaluation, mainly for the object of evaluation activities, in which there is the problem of evaluation subject and evaluation object, and thus the good or bad obtained as the final judgment result, which is the change that occurs in the value subject and the value object. In addition, there are similarities and differences in evaluation methods, and there are quantitative and nonqualitative methods. Simply put, value determination of things by numerical and quantitative methods is called quantitative evaluation, and this method is generally for clarifying the level of the object's memory ability and has great limitations, while value determination by non-numerical and quantitative methods is called qualitative evaluation.

The nonquantitative evaluation to be discussed in this thesis is not to use objective teaching evaluation as the measurement index, but to use effective evaluation tools to make a qualitative analysis of foreign language translation teaching and timely feedback to evaluate teaching to develop evaluation.

In previous years, teaching evaluations were based on the subjective perceptions of listening experts or teachers to evaluate the foreign language translation teaching process, but the obtained results often deviated from the actual situation, and for this reason, researchers have proposed many index systems for classroom teaching evaluation. However, most of the existing studies on the evaluation index systems of foreign language translation teaching in secondary schools are not relevant and cannot accurately evaluate the effectiveness of foreign language translation teaching in other schools [15]. Based on the practical experience of teaching in secondary schools and the opinions of other English teachers and experts, the authors construct an index system that is consistent with the evaluation of foreign language translation teaching to facilitate future evaluations. Therefore, this chapter will elaborate on the principles of index selection and index screening of the foreign language translation teaching evaluation system.

There are many factors affecting the evaluation of foreign language translation teaching in colleges and universities, it is necessary to select indicators from many aspects and scopes at the same time, and the results of English classroom teaching evaluation should be considered as much as possible in the process of selecting indicators to provide a reference for future classroom teaching evaluation. For the process of indicator selection, classroom teaching evaluation should have certain feasibility, considering whether the data of certain indicators are easy to obtain and whether the indicator factors are clear, so whether the indicators are reasonable, the evaluation data collected will not have any value role. When English classroom teaching indicators are selected, the maximum possible to achieve the simplicity for the total number of indicators selected, if all the indicators are selected into the framework of indicators, it will lead to the loss of a role of the indicators selected at the beginning, so take its brief and clear indicators more and reduce the work of the evaluator, as shown in Table 1.

By extracting the indicators of foreign language translation teaching evaluation in universities, the expert evaluation indicators are integrated. In the selection of each index, the index that occupies a small proportion is identified through experiments and sieved out to obtain expert evaluation indexes. The questionnaires were mainly distributed by e-mail after class, and 100 expert questionnaires were distributed in total.

The analysis of the results shows that most of them think that some indicators have higher total scores and the scores are basically distributed above 240, but some other indicators have lower scores, all of them are below 120, so the indicators distributed above 240 are chosen as reserved indicators, and the indicators derived are teaching plan, and scientific and reasonable classroom teaching. Consideration should also be given to the use of multi-level comments to give judgments and to determine the membership function for each comment level. The ratio of English to Chinese dictation in answering questions is shown in Figure 1.

The value orientation of foreign language translation in higher education in learning evaluation is firstly positioned on the experience of students' learning situation and

Table 1: The present system of expert evaluation indexes.

Main target	First-level indicator	Secondary indicators
Translation level	Teaching plan	Scientific and reasonable classroom teaching. Appropriately adjust the teaching plan.
	Teaching means	The use of multimedia teaching and explanations is completed on time. Help students expand the horizons of English classroom teaching.
	Teaching attitude	Meticulous teaching. Explain in simple language. Many examples.
	Class performance	Pay attention to students' listening, speaking, reading, and writing skills.

learning process. Evaluation is not only to give results, but also to stimulate students' motivation, creativity, and curiosity in the learning process. Therefore, the assessment of foreign language translation in higher education should consider the collection and use of information, the synthesis and transfer of knowledge, and the judgment and solution of problems. The value orientation of the evaluation of foreign language translation in higher education is focused on the development of individual development skills. Education is a process that has no end, people will always be aware of learning new things and new knowledge. The individual's ability to develop themselves is cultivated so that they can get the fullest development in all aspects of their life. Therefore, foreign language translators in higher education should consider the learner's ability to learn, social skills, and adaptability in the evaluation of learning.

The study developed an evaluation index system reflecting the characteristics of ubiquitous learning, determined the corresponding affiliation function, realized the unified processing of different types of qualitative and quantitative indicators, and detailed the specific steps and operation process of fuzzy comprehensive evaluation [16]. In the link of index assignment under fuzzy comprehensive evaluation, the subjective and objective index assignment method combining hierarchical analysis and principal component analysis is proposed. The method combines the evaluation matrix and the sample matrix, based on objective data, combines with expert opinions, and finally deduces the comprehensive weights.

Before formulating the evaluation indexes of foreign language translation in higher education, we should first study and analyze the characteristics of foreign language translation in higher education, and then set reasonable evaluation indexes that can reflect all the influencing factors according to their learning characteristics.

The learning of foreign language translation in higher education is different from other digital learning such as online learning and mobile learning, which have their special characteristics. The shorter the short axis of the ellipse is, the ellipsoid surface will be very steep in the direction of the short axis and very flat in the long axis direction. Such a loss plane will be very steep, many detours will be taken during the optimization process, and the calculation efficiency will be greatly reduced. Through context-aware technology and wireless network technology, it can sense learners' situation in the real world, provide adaptive information and services more actively based on learners' context, and record learners' behavior and information in the real world, creating a highly interactive contextual learning for learners that is not limited by time and space.

Through the first two steps, several indicators have been collected and selected for generalization. The indicators with the same meaning and different expressions were combined into one indicator, and the most appropriate one was selected. Several indicators with different evaluation perspectives were divided as first-level indicators, and then the indicators with strong correlation were combined under the same higher-level indicator. Using the method of induction and deduction, the index system framework of 5 primary indicators, 11 secondary indicators, and 34 evaluation parameters was finally formed.

Indicator weight refers to the importance or contribution of each indicator in the indicator system and is a value assigned to measure the importance or position of an indicator in the learning evaluation indicator system. The weight of the indicator reveals the objective imbalance of each indicator, reflecting the difference in the influence of its corresponding factors on the realization of meaningful foreign language translation in learning in universities. The values of weights are expressed in the form of decimals, integers, and percentages [17].

In general, the decimal form is mostly used to express the weights. This is because it not only is more convenient and suitable for allocation but also more accurately reflects the value difference of each index. When assigning weights, the group of indicators at the same level is often considered as a whole, and the total weight of this whole is 1, as shown in Figure 2.

The basic idea of principal component analysis is to extract as few major evaluation factors as possible from all the originally proposed evaluation factors. The main evaluation factors should reflect the comprehensive information of the original m evaluation factors, and the information reflected by the n main evaluation factors should not overlap with each other. The weights are then assigned based on the actual data of the evaluation sample and the contribution rate of each major index in the sample. In summary, the principal component analysis method is used to filter several main components from multiple original indicators with the help of an orthogonal transformation.

The evaluation of the original indicators is achieved by analyzing and interpreting the main components. The evaluation index system in this paper contains more than thirty evaluation parameters, and such many evaluation indexes should be chosen as the assignment method that can reduce the calculation volume and the difficulty of the analysis process. And the principal component analysis

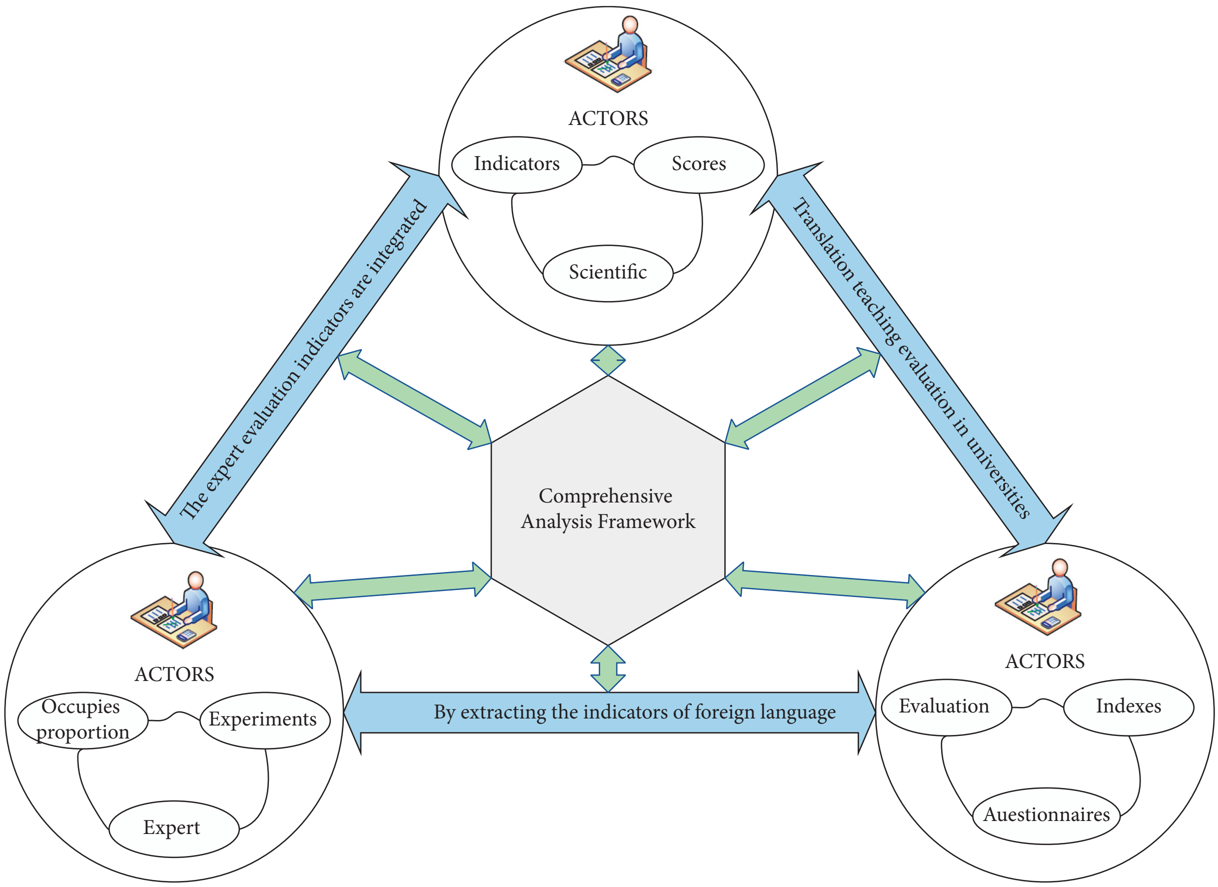

FIGURE 1: The process of assessing the level of foreign language translation in colleges and universities.

method is an effective tool suitable for setting the weights of many indicators in the learning evaluation of foreign language translators in universities.

4. Fuzzy Comprehensive Evaluation Random Matrix Model Design

Firstly, the total score F of the second-level indexes of experts is calculated, then the weights of the second-level indexes of experts' evaluation are calculated, and finally, the weights of the first-level indexes of experts' evaluation are calculated. In addition, students and teachers can also refer to this calculation process to get the corresponding scores of second-level evaluation indexes, the weights of first-level indexes, and the weights of second-level indexes [18]. Therefore, 15% of the test set is randomly selected during the experiment. The relationship matrix is obtained from the evaluation vectors in the evaluation of foreign language translation teaching in universities. First, the affiliation matrix is determined. Taking experts as an example, the i-th second-level evaluation index evaluates the first-level evaluation index N_{ijz} and gets a fuzzy vector R relative to the set of comments M. All rows in the expert matrix are the results of an evaluation against all indicators, and in addition, the matrix includes all the information obtained by evaluating the set of evaluation results M, against the set of evaluation indicators N, as shown in the following equation:

$$r_{\mathrm{ijz}} = \frac{N_{\mathrm{ijz}}}{M}. \tag{1}$$

The evaluation results of experts, students, and teachers are obtained separately, and the fuzzy relationship matrix Ri between the secondary indicators and the primary indicator rubrics is established. There are m evaluation levels and n second-level evaluation indicators, then the fuzzy relationship matrix R_i of the first-level indicators, as shown in the following equation:

$$R_i = \begin{bmatrix} r_{i11} & r_{i12} & \cdots & r_{i1m} \\ r_{i21} & r_{i22} & \cdots & r_{i2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{in1} & r_{in2} & \cdots & r_{inm} \end{bmatrix}. \tag{2}$$

To determine the weights of foreign language translation in learning evaluation indexes in universities more accurately, this paper combines the weights calculated separately by hierarchical analysis and principal component analysis to obtain the final weights of the indexes. This combination of subjective and objective weighting methods complements each other, which not only can avoid the subjective arbitrariness of the weight setting process, but also solves the problem that the weights and the importance of indicators contradict each other.

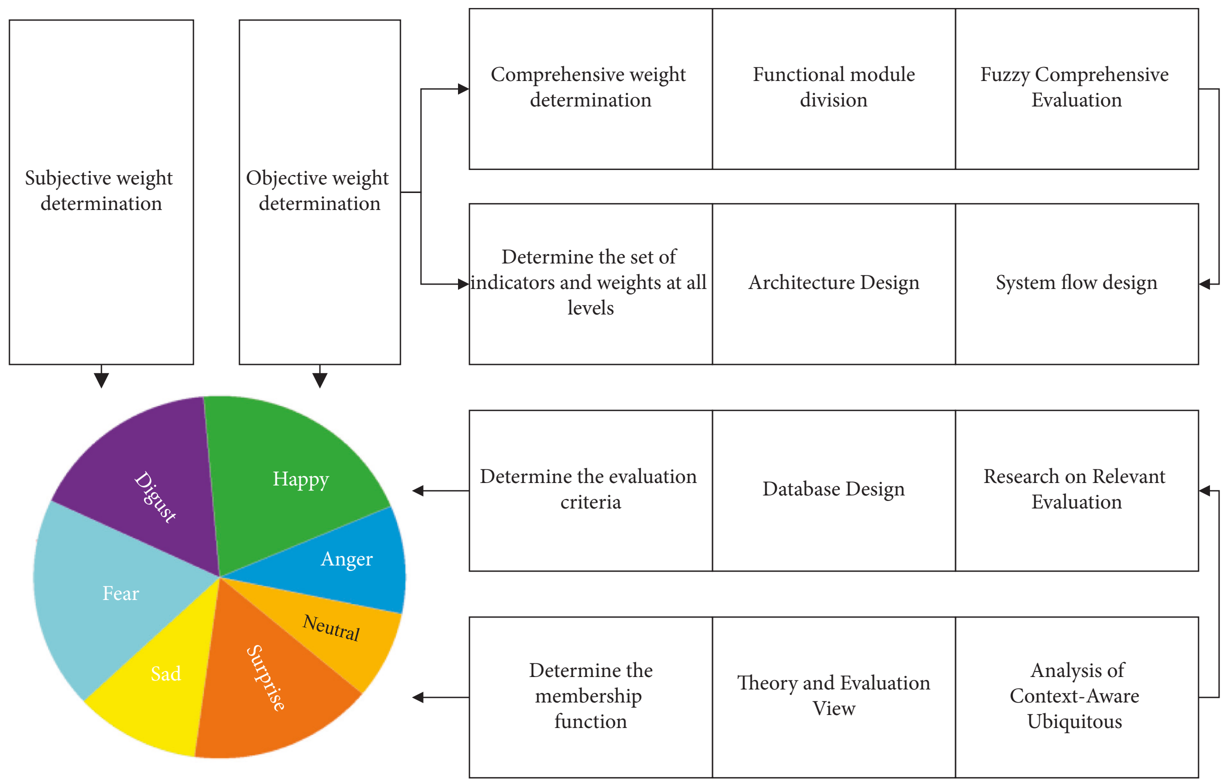

Figure 2: Flowchart of the overall study.

$$\theta_i = \frac{w_i b}{\sum_{i=1}^{m} w_i b}. \tag{3}$$

Comparing objects with each other is the basic idea of the binary comparison method. By sorting the order of these objects belonging to a certain characteristic, the general shape of the affiliation function is determined. The binary comparison ranking method can be further divided into priority relationship ordering method, comparison averaging method, relative comparison method, etc. Using fuzzy comprehensive evaluation, the influencing factors involved in the evaluated object should be determined first and the set of evaluation indexes should be established. It should also be considered to give the evaluation with multi-level rubrics and determine the affiliation function of each rubric level [19]. Translation researchers mostly focus on the subjective criticism and error analysis of translations, and they are dominated by qualitative research. TQA has not received due attention and has not fully played its role. When the evaluation subject contains multiple influencing factors, the weight proportion of each factor should be set because every single factor is of a different importance in the total evaluation. Based on the above, a fuzzy evaluation matrix is established, and then the quantified rubric grades are introduced into the fuzzy matrix to obtain the comprehensive evaluation results, as shown in Table 2.

Determine the affiliation degree of each index score of the evaluated object to the evaluation grade, and then obtain the fuzzy matrix R reflecting the fuzzy relationship from U to V.

Table 2: Translation secondary index scores.

Index	Grade	Fraction
Validity	Good	86.5
Constructive	Excellent	97
Positivity	Excellent	93.1
Interactivity	Good	83.3
Adaptability	Good	82.1
Situational awareness	Excellent	93.8
Knowledge transfer	Good	86.4
Understanding of learning terminals	Excellent	91
Use of learning terminals	General	82.1
Learning environment preferences	Excellent	94.4
Learning terminal preferences	Excellent	97.9

$$U = A \cdot V. \tag{4}$$

According to the evaluation result vector, the result of the fuzzy comprehensive evaluation is determined by the weighted average method or the maximum subordination method. In general, the weighted average method is used to calculate the final evaluation result by multiplying the evaluation result vector M with the rank score matrix P.

The concept of affiliation and several common methods of determining affiliation have been introduced above, but the above methods are still based on practice and experience, and no method is mature and effective [20]. The process of determining the affiliation function should be objective, but the process of determining the affiliation function is subjective because different people have a different understanding of fuzzy concepts. Different people will establish different affiliation functions, if they can solve the problems in the actual fuzzy information which is a proven method, as shown in Figure 3.

The fuzzy comprehensive evaluation of foreign language translation in learning in colleges and universities is divided into multiple levels, the evaluation factor values at the evaluation parameter level are obtained directly statistically, while the evaluation factor values at the level above the second level are obtained through the first-level fuzzy comprehensive evaluation process [21]. Because ambiguity is an inherent property of all languages, and translation is an activity between different languages, ambiguity is inevitable. Therefore, to obtain accurate comprehensive evaluation results, the affiliation function needs to be established when performing fuzzy comprehensive evaluation at each level.

The results of the above data show that the student excels in understanding and using learning terminals, indicating that a student is a developmental person suitable for the modern technology-supported learning environment and that good use of learning tools can help learners achieve meaningful learning more effectively. This should be emphasized in the evaluation feedback so that students are fully aware of their strengths [22]. At the same time, the score data for the secondary indicators also indicate that the learning model of foreign language translation in learning in higher education is applicable and meaningful for this student. The student has a good motivation to learn when conducting the study, which can effectively assist the learner in completing knowledge transfer.

5. Analysis of the Results

5.1. Results of the Fuzzy Integrated Judgment Random Matrix Model Performance. The relationship between the maximum eigenvalue and the minimum eigenvalue of the Hessian matrix is also a key factor in determining the loss plane. We know that in the quadratic loss function, the loss plane is an ellipse-like shape, where the minimum eigenvalue determines the direction of the long axis of the ellipse, and the length of the long axis is inversely proportional to the square root of the minimum eigenvalue. Correspondingly, the short axis and the maximum eigenvalue have the same relationship.

When studying the relationship between the maximum eigenvalue and the minimum eigenvalue, two relationship usually studied. The first is the difference between the two, but in deep neural networks, the difference between the two is very close to the maximum eigenvalue. The larger the difference between the two, the shorter the short axis of the ellipse, and the ellipsoidal plane will be very steep in the direction along the short axis and very flat in the direction of the long axis so that the loss plane will be very steep, many detours will be taken in the optimization process, and the computational efficiency will be greatly reduced. The second one is to calculate the standard condition number, which can reflect the stability of the network. Again, only one standard condition number is obtained after each network training, so we calculate the distribution of the standard condition number for 500 repetitions of the experiment, as shown in Figure 4.

In the decision-making of the multi-objective scheme, it is necessary to determine the weights of the indicators according to the characteristics of the distribution of the values of each objective and the degree of importance. Usually, the methods of determining the weights are the method of subjective determination by experts by the subjective determination and the method of objectively determining the weights of the indicators according to the degree of deviation of the distribution of the values of the indicators of each scheme. Such mappings are typically represented by numerical functions containing several undetermined parameters, the estimated values of which can be determined using an associated learning algorithm. The latter is the objective weighting method, the essence of which is to maintain the basic equivalence of the influence of each indicator in the comprehensive evaluation. However, this method is not suitable for the case where the importance of each indicator needs to be divided into different levels. The objective weighting method, which is more commonly used nowadays, is proportional to the deviation margin. However, since most of the sample segments of the indicators are not uniformly distributed, the proportional weighting has obvious disadvantages. The weights of the evaluation indicators are constructed using the vector cosine. The method was applied to the weighting of an investment scheme, and the results obtained were consistent with the experts' opinions on the ranking of the weights of the indicators, indicating that the method is practical and feasible.

In the clustering of training samples and test samples of handwritten data, respectively, all four algorithms achieved better clustering results. Since the training sample set has a larger sample size and contains more information, the overall clustering results of all four methods are better than those of the test samples, improving the correct clustering rate by ten percentage points. Further comparison shows that for the matrix dataset used in this experiment, the Gaussian mixture model fuzzy algorithm based on K-L information entropy regularization has a better clustering effect than the traditional Gaussian mixture model; the matrix normal mixture model has a better effect than the traditional Gaussian mixture model and GMM-KL-FCM, the best performing model is the one combining the matrix normal mixture model and K-L information entropy MVMM-KL-FCM, the selected parameter λ takes the value of 1.2, and the experimental results are overall in line with the expected content, as shown in Figure 5.

Based on the previous step, matrix normal distribution is introduced again to deal with the datasets in the form of matrices commonly used in practical research, the relevant principles of matrix normal distribution are introduced, and the matrix normal mixture model is induced. After that, the fuzzy c-means algorithm based on K-L information entropy regularization and matrix normal mixture model is introduced by combining the fuzzy c-means algorithm and K-L information entropy. Moreover, by using the mathematical nonlinear programming theory to obtain the solution of the optimization problem, the process is relatively easy to program. The clustering of the matrix handwritten dataset is empirically demonstrated using several models introduced

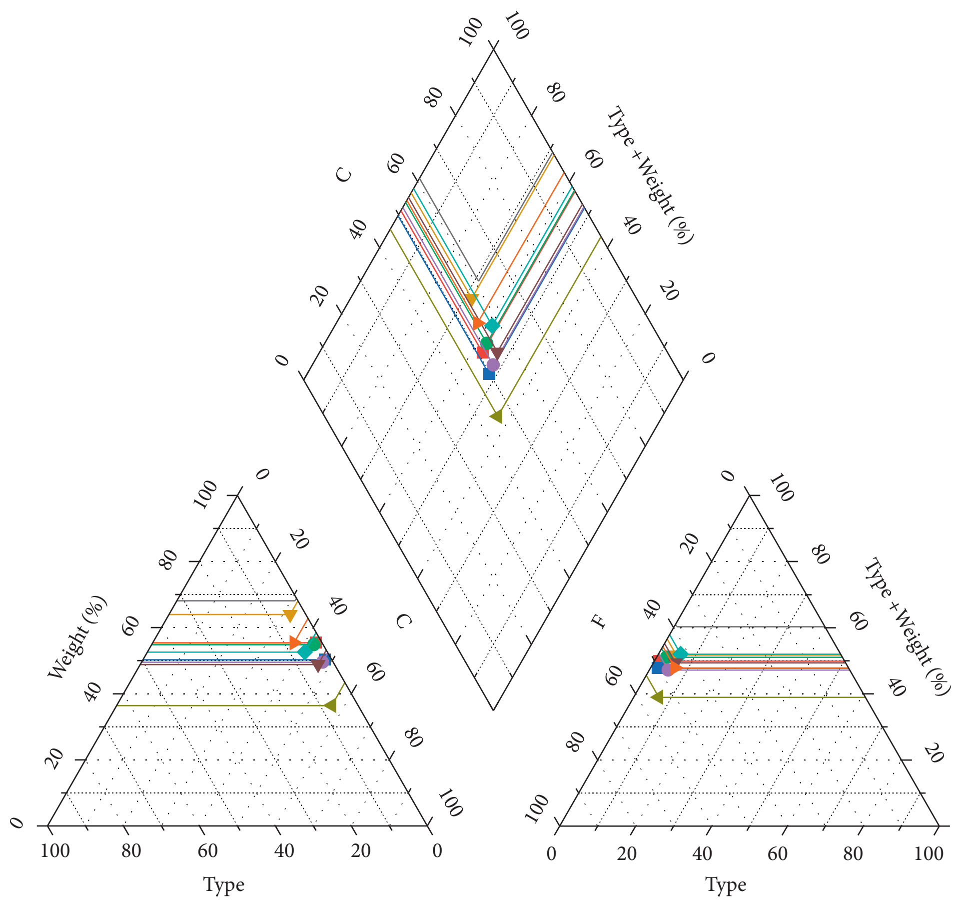

Figure 3: Weight and affiliation degree under indicators.

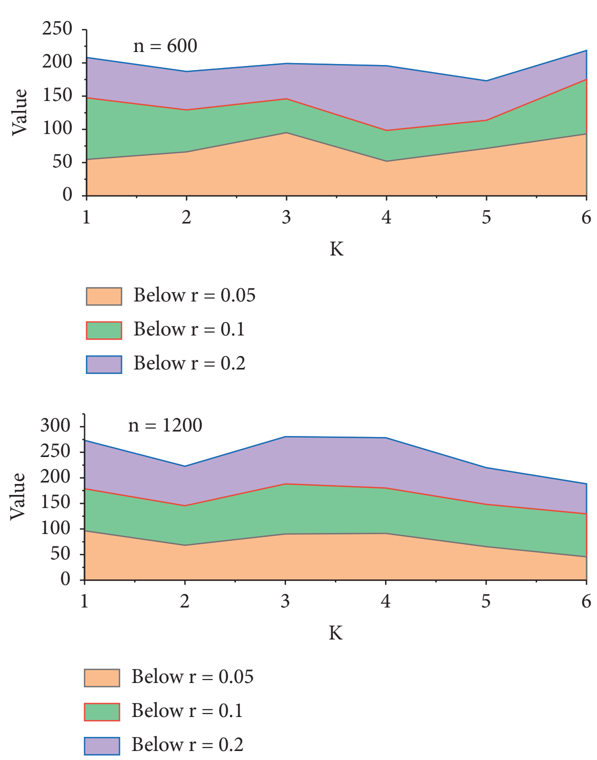

Figure 4: Empirical level under 200 simulations.

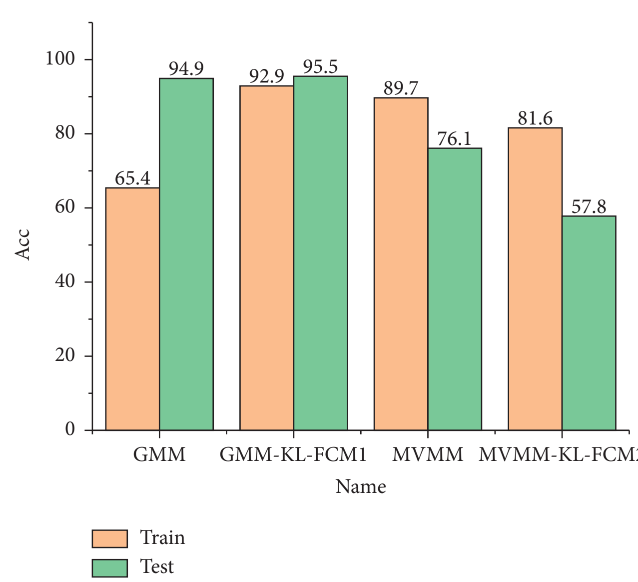

Figure 5: Correct clustering rate of several algorithms on the translated dataset.

in the previous paper, comparing the effect of the parameter λ taking on the fuzzy algorithm and the performance of different algorithms on this dataset, and experimentally verifying that the improved fuzzy c-mean algorithm based on K-L information entropy regularization and matrix normal mixed model has a better clustering effect.

The objective weight values are obtained utilizing principal component analysis, and the calculation process is carried out layer by layer from low-level indicators to high-level indicators. First, for the raw achievement data of the lowest level evaluation parameters, the correlation coefficient matrix and the eigenvalues of the correlation coefficients are calculated according to the principal method of principal components.

5.2. Results of Foreign Language Translation-Level Assessment in Higher Education. In the confusion matrix, the horizontal coordinate indicates the experimentally predicted modulation mode, the vertical coordinate indicates the real modulation mode, and the darker the color of each square in the matrix, the higher the probability that the corresponding real modulation mode is judged as the corresponding predicted modulation mode. Therefore, for a network, the confusion matrix is a diagonal array and the network has the best prediction performance. In this experiment, it can be observed that as the signal-to-noise ratio increases, the prediction performance of the network gets better. The resulting good and bad results are used as the final judgment result, that is, the changes in the value subject and the value object. However, in general, the network does not classify well for both modulation types, QAM16 and QAM64, and always misclassifies between them. This is because both modulations belong to QAM modulation, but different binary methods are used. Although the network designed in this paper cannot identify the specific type of modulation, it can identify them both as QAM modulation more accurately and then further judge them based on the signal constellation diagram, which can further improve the classification accuracy of the system.

The approximate Hessian matrix was calculated after the experimental convergence was completed because the network parameters were large, but the hardware of the experiment was limited, so 15% of the test set was randomly selected during the experiment.

From Figure 6, we can see that the distribution of the eigenvalues of the experimentally obtained Hessian matrix is still consistent with our theoretical analysis results, with many eigenvalues concentrated around 0. There are still many smaller negative eigenvalues, but this time there are some larger numbers in the negative eigenvalues, around -0.1. Such results remind us that we need to pay attention to the minimum eigenvalues of the network as well. The minimum eigenvalues may change with the structure of the network and the optimization of the network, and there is still room for improvement in the optimization of the network in this experiment.

For the analysis of larger eigenvalues, again, the larger eigenvalues in this experiment are orders of magnitude larger than the larger eigenvalues in the MNIST dataset, which of course has a lot to do with the complexity of the network; as the network layers deepen, the Hessian matrix will amplify the larger eigenvalues as they are passed from

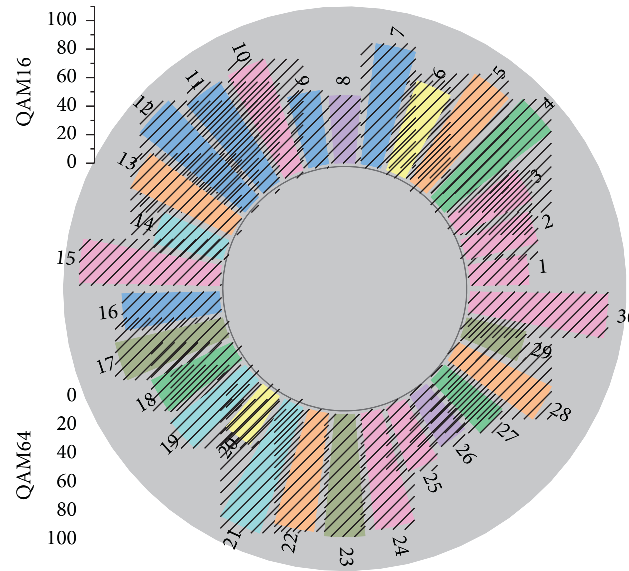

Figure 6: Distribution of translation-level values of the depth residual network matrix.

layer to layer. The maximum eigenvalue is still an important factor in the deep learning optimization problem, which also provides ideas for further improvement of the optimization algorithm in the future, such as limiting the maximum eigenvalue of the Hessian matrix in each iteration of the gradient descent.

This combination of qualitative and quantitative methods enables people not only to see quantitatively which translation is good and which is not, but also to grasp qualitatively the advantages and disadvantages of each translation. Most importantly, this method is widely applicable to different types of texts, and we only need to assign different weight values to each specific evaluation parameter according to the different characteristics of different texts, as shown in Figure 7.

Based on the above analysis, we can conclude that the application of fuzzy science to TQA is practical and easy to operate. Although the method still cannot be accurate and objective, for example, the division of the affiliation function, the determination of the evaluation factors, and the establishment of the weight set are all artificially specified. The role of the human is to constantly adjust and correct these deficiencies according to the translation practice experience, and the machine is only responsible for the calculation; however, it considers all the factors that affect the objectivity of the evaluation, so it is relatively more objective. This combination of the qualitative and quantitative model makes the comparison between different translations easier and more intuitive; it is also widely applicable and can be used for translation assessment in translation examinations, competitions, etc.

6. Conclusion

In this paper, we first constructed a fully connected network to validate the random matrix theory analysis method and dealt with the most classical multi-classification problem in

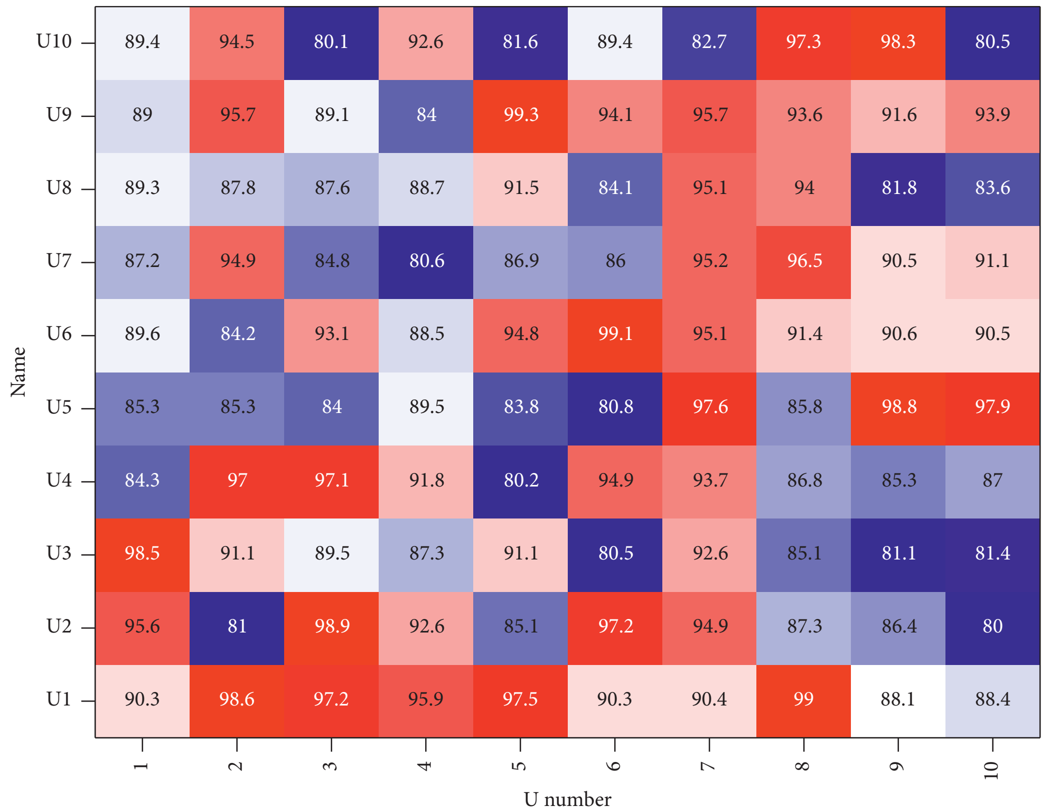

Figure 7: Foreign language translation-level evaluation results.

deep learning. The exact Hessian matrix is obtained, the finite spectral distribution of the matrix, the eigenvalue extremum distribution, and the standard conditional number distribution of multiple experiments are obtained, and the experiments prove that the random matrix theory analysis method is feasible and effective. The modulated signals in modern wireless communication are diverse and complex, and it is very important to carry out accurate modulation classification and detection of the signal processing at the shattered receiver. It is impossible to accurately evaluate the teaching effect of foreign language translation in other schools. Based on the practical experience of teaching in middle schools and the opinions of other English teachers and experts, the author constructs an index system that conforms to the evaluation of foreign language translation teaching, which is convenient for evaluation in the future. It provides a theoretical basis for further optimization of wireless communication networks and provides a reference for future theoretical research. The research in this paper shows that it is necessary and feasible to apply the fuzzy comprehensive evaluation method to the comprehensive evaluation of college students. The research of this paper has achieved certain results, but there are still many areas that need to be improved due to the author's level and limited research time. The quantitative aspects of the indicators also need to be carried out in more in-depth research to facilitate the application of the method. More work should be done on how to translate the more complex mathematical algorithms into educational work practices so that these methods can have strong practicality.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have conflicts of interest.

Acknowledgments

This work was supported by 2020 vocational education teaching research reform project of Hunan Provincial Department of Education "Research on the innovation of teaching mode of deep learning of ESP course in Higher Vocational Colleges under the background of Teaching models, material, methods" reform (Subject No: zjgb2020437), Research on language demand and supply strategy of "Export of Hunan Enterprises" (Subject No: XH2021235) in the scientific research planning project of Hunan Vocational Education and Adult Education Association in 2021, and Research on the "three double" talent training system of language under the background of the "the Belt and Road" (Subject No: 19WLH22) in foreign language research joint project of Hunan Social Science Fund in 2019.

References

[1] Z. Wang, "Fuzzy comprehensive evaluation of physical education based on high dimensional data mining," *Journal of Intelligent and Fuzzy Systems*, vol. 35, no. 3, pp. 3065–3076, 2018.

[2] N. A. Li, "A fuzzy evaluation model of college English teaching quality based on analytic hierarchy process," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 2, pp. 17–30, 2021.

[3] J. Shu, "A POA theory-based network teaching mode for English course in higher vocational college," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 17, no. 01, pp. 224–238, 2022.

[4] J. Yuan, W. Li, B. Xia, Y. Chen, and M. J. Skibniewski, "Operation performance measurement of public rental housing delivery by PPPS with fuzzy-AHP comprehensive evaluation[J]," *International Journal of Strategic Property Management*, vol. 23, no. 5, pp. 328–353, 2019.

[5] C. Rao, Y. He, and X. Wang, "Comprehensive evaluation of non-waste cities based on two-tuple mixed correlation degree," *International Journal of Fuzzy Systems*, vol. 23, no. 2, pp. 369–391, 2021.

[6] W. Na and Z. C. Zhao, "The comprehensive evaluation method of low-carbon campus based on analytic hierarchy process and weights of entropy," *Environment, Development and Sustainability*, vol. 23, no. 6, pp. 9308–9319, 2021.

[7] F. Carrillo-Perez, O. E. Pecho, J. C. Morales et al., "Applications of artificial intelligence in dentistry: a comprehensive review," *Journal of Esthetic and Restorative Dentistry*, vol. 34, no. 1, pp. 259–280, 2022.

[8] D. Cao and Y. Guo, "Algorithm research of spoken English assessment based on fuzzy measure and speech recognition technology," *International Journal of Biometrics*, vol. 12, no. 1, pp. 120–129, 2020.

[9] H. M. Balaha, H. A. Ali, and M. Badawy, "Automatic recognition of handwritten Arabic characters: a comprehensive review," *Neural Computing & Applications*, vol. 33, no. 7, pp. 3011–3034, 2021.

[10] K. Chen, D. Liu, Z. Fan, X. Chen, and F. Khan, "Risk analysis of oilfield gathering station," *Process Safety Progress*, vol. 38, no. 1, pp. 71–77, 2019.

[11] G. Sun, C. C. Chen, and S. Bin, "Study of cascading failure in multisubnet composite complex networks," *Symmetry*, vol. 13, no. 3, p. 523, 2021.

[12] J. Yang and X. Wang, "Investigation and research on student satisfaction evaluation of campus node square—taking southwest university of science and technology as an example," *Open Journal of Social Sciences*, vol. 09, no. 6, pp. 385–396, 2021.

[13] A. K. Ozcanli, F. Yaprakdal, and M. Baysal, "Deep learning methods and applications for electrical power systems: a comprehensive review," *International Journal of Energy Research*, vol. 44, no. 9, pp. 7136–7157, 2020.

[14] W. Ali, W. Tian, S. U. Din, D. Iradukunda, and A. A Khan, "Classical and modern face recognition approaches: a complete review," *Multimedia Tools and Applications*, vol. 80, no. 3, pp. 4825–4880, 2021.

[15] M. Masdari and H. Khezri, "Service selection using fuzzy multi-criteria decision making: a comprehensive review," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 2, pp. 2803–2834, 2021.

[16] J. Li and K. Xu, "A combined fuzzy DEMATEL and cloud model approach for risk assessment in process industries to improve system reliability," *Quality and Reliability Engineering International*, vol. 37, no. 5, pp. 2110–2133, 2021.

[17] A. G. Hussien, M. Amin, and M. Abd El Aziz, "A comprehensive review of moth-flame optimisation: variants, hybrids, and applications," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 32, no. 4, pp. 705–725, 2020.

[18] M. Tavana, A. Shaabani, M S. Mansouri, and N. Varzgani, "An integrated fuzzy AHP- fuzzy MULTIMOORA model for supply chain risk-benefit assessment and supplier selection," *International Journal of Systems Science: Operations & Logistics*, vol. 8, no. 3, pp. 238–261, 2021.

[19] S. Yu, "Application of computer information technology in college physical education using fuzzy evaluation theory," *Computational Intelligence*, vol. 37, no. 3, pp. 1181–1198, 2021.

[20] S. Bin and G. Sun, "Optimal energy resources allocation method of wireless sensor networks for intelligent railway systems," *Sensors*, vol. 20, no. 2, p. 482, 2020.

[21] M. Hamadache, J. H. Jung, J. Park, and B. D. Youn, "A comprehensive review of artificial intelligence-based approaches for rolling element bearing PHM: shallow and deep learning," *JMST Advances*, vol. 1, no. 1-2, pp. 125–151, 2019.

[22] A. Rehman, S. Naz, and M. I. Razzak, "Writer identification using machine learning approaches: a comprehensive review," *Multimedia Tools and Applications*, vol. 78, no. 8, pp. 10889–10931, 2019.