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Article

Minimizing Emotional Labor through Artificial Intelligence for Effective Labor Management of English Teachers

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Abstract: Combinatorial mathematics is a versatile field that can provide valuable insights and techniques in various aspects of artificial intelligence and educational research. We focus our attention on the exploration of the mechanism of the role of teachers' emotional labor In this paper, we merge two parts of data, predicted and formally administered, based on the optimization and management of artificial intelligence English teachers' emotional labor for the corresponding statistical analysis. Yes individual college English teachers are working for non-interpersonal issues for emotional regulation, temporarily restraining anger and cursing impulses, and communicating with students in a pleasant manner. In the case study of this paper, a teacher repeatedly failed in teaching, but he restrained his frustration and continued to work hard, and finally finished.

Keywords: artificial Intelligence; optimization; statistical Analysis.

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1. Introduction

In the early tenth century, Taylor opened the door to "scientific management" by advocating the use of scientific methods to design work, select employees, and standardize work processes to increase employee productivity [1]. The organization was seen as a rational entity, and the emotional component was completely excluded. In the organization, effective employees must remain rational and objective, not "emotional"; if emotions appear, they should be strictly controlled so as not to interfere with rational organizational functions; and employees seem to be an absolutely rational decision-maker who will make the most optimal decisions to maximize benefits [2–4]. This view has led many scholars to focus their research on organizational behavior on how to design work processes to maximize work productivity, while employees are just people who perform work, and their emotions are not as important as the work design itself. Mcgregor (1957) and Maslow (1965) wrote books on humanistic management, which led to the trend of humanism in the corporate world [5]. Many employee-oriented management concepts, such as employee assistance programs and quality of work life), have been proposed, The spirit of these management concepts is that organizations should not only pursue performance, but also pay more attention to employee satisfaction, happiness and centripetal force, so that employees can be happy [6–9]. Emotions play an important role in human communication activities. Expressing one's emotions to others can be done through some important non-verbal cues (e.g., expressions, gestures, etc.) that are read by the receiver and can convey and explain the meaning of an emotion being felt by the sender [10–12]. However, the emotions that people show are not necessarily the emotions that they actually experience, and likewise, the emotions that people experience are not always the emotions that they show, and in 1969, Ekman and Friesen used the "affectiveor emotion display rules" to explain this phenomenon.) In 1969, Ekman and Friesen used the term "affectiveor emotion display rules" to explain this phenomenon, thus introducing the concept of emotion display rules, and subsequent researchers have been deeply interested in this field of study and have developed their own understanding of the meaning of emotion display rules from different perspectives and fields, including, of course, emotion display rules in work situations [13–15]. Ekan and Friesen coined the term "cultural expression rules" to describe cultural differences in human expression of facial emotions, which they believe are acquired in early childhood, help individuals manage and regulate their own emotional expression, and are dependent on the social environment [16]. The earliest evidence to support this idea appears in a study by Friesen, who tested the expression of natural emotions in Americans and Japanese when they watched a highly stressful movie in two conditions. First, the subjects watched alone, and then an older male subject watched with them [17]. Ekman and Friesen argued that in the first condition, since the subjects were alone and no social environment existed, they did not need to regulate their expressions according to the emotion expression rules, and the expression rules did not work. In the second condition, H himself adjusted his facial expressions according to the expression rules, and concealed his negative emotions in front of the experimenter because of the presence of an older person and the existence of a social environment. According to the different tasks achieved by emotional labor, emotional labor includes positive emotional labor, negative emotional labor, and expression-neutral emotional labor. Positive emotional labor is used to increase human contact, and the main task is to express a positive and pleasant emotional work atmosphere, such as the work of flight attendants; negative emotional labor is used to express intimidation or suppression, and the main task is to express a negative Negative emotional labor is used to express intimidation or suppression, and the main task is to express negative emotions and work atmosphere, such as the work of teachers. Neutral emotional labor is used to convey authority relationships and to demonstrate fairness and professionalism, such as the work of a judge. When dealing with students, members are mostly expected to express a more positive emotional.

2. Related Work

Following Hochschild's concept of emotional labor, Rafaeli and Sutton conducted qualitative studies on different occupations, which drew the attention of researchers to emotional labor. They defined emotional labor as "the effort to plan and control an individual's emotional behavior to meet organizational requirements in the process of interpersonal interaction. [18] pointed out that surface and depth behaviors are the two dimensions of emotional labor and proposed a two-dimensional emotional labor theory according to the different focus. [19] classified emotional labor as: genuine, suppress, and fake according to the degree of matching between employees' internal experience and organizational requirements. When the individual experience is consistent with the presentation rules, the emotion expressed by the employee is genuine; when the individual does not experience the emotion that the organization needs to express, the emotional expression performed is faking; when the individual experience does not match the organization's presentation rules, the individual has to suppress the emotion that the organization does not need, and at the same time, he or she also needs to fake the emotion that the organization needs. [20] fused electrodermal, respiratory, and electrocardiographic signals of singers successfully identified four basic emotions of singers Rigas et al. used KN and RF random forest algorithms to identify fused electrocardiographic, electrodermal, and respiratory signal features, and finally achieved an average recognition rate of 60% on nine categories of emotions. [15] firstly constructed a speech feature extraction network and an image feature extraction network respectively, then did cascade fusion of the middle layer features of the two networks, and finally fed the fused features into a 2-layer LSTM network to extract the hidden temporal information and complete the emotion classification. In the area of speech and text bimodal emotion recognition: [16] proposed a three-convolutional plus attention mechanism recognition method, firstly, both speech and text are used to extract features using convolutional networks, and then the intermediate level features of both are fused to obtain the attention distribution using the attention mechanism. In [17], a recognition method using a dual RNN plus attention mechanism is proposed. First, the speech and text information are encoded using an RNN network, then the attention score is calculated for the hidden state of each text time step using the speech encoding vector and the hidden state of the text at each time step, then the attention distribution is linearly weighted to the hidden state of the text, and finally the fused features containing the attention distribution are is used for emotion classification [18].

3. Text word representation

This section focuses on how to represent the features of words in text, that is, to explore word representation methods. The early word representation researcher has one-hot representation, word frequency-inverse document frequency representation, topic model, etc. The current research trend is to use deep learning technology to represent word embedding based on language model, and the representative researcher has word2vec word embedding, Glove word embedding, etc.

3.1. TF-IDF indicates

Term Frequency- Inverse Document Frequency (TF-IDF) representation is a distributed text representation method based on statistical means, which can take into account the semantic information of words to a certain extent, and can measure the ability of a word to distinguish the corpus, and can be used as a classification 80 TF refers to how often a word appears in a document, and it is the result of normalizing the number of words to prevent it from biasing toward documents with more words. The importance of a word t in a document can be expressed by its word frequency. The word frequency is calculated as follows:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{1}$$

The inverse document frequency can be used to measure the prevalence of a term. The formula for calculating the inverse document frequency is as follows:

$$idf_i = lg\frac{|D|}{1 + |j : t_i \in d_j|} \tag{2}$$

Where $|D|$ denotes the number of documents in the corpus and the absolute value of the denominator denotes the number of documents containing the word . The word frequency of a word in a document inverse document frequency is the product of its word frequency and its inverse document frequency:

$$tfidf_{i,j} = tf_{i,j} \times idf_i \tag{3}$$

The basic idea of using TF-DF to represent a word is that if a word appears more frequently in one document and less frequently in other documents, it means that it will produce a high weighted TF-IDF value. A high weighted TF-IDF value tends to filter the common words and leave the important words. Therefore, words with higher TF-IDF values are considered to have better ability to distinguish text and can be used for text classification.

3.2. Theme Model

Topic modeling is a series of documents to discover the abstract theme of the statistical model, it is built on the idea that if a document has a central idea, then some words in this document will certainly appear very high frequency, the theme model is an attempt to design a mathematical model to describe this feature. The most commonly used topic modeling technique is the Latent Dirichlet Distribution (LDA), the goal of the LDA algorithm is to find the probability distribution of topics in each document and the probability distribution of topic words in each topic based on a predetermined number of topics: Assuming that the prior probability distribution of the topic is the Dilley distribution, then for any document d, its topic probability distribution t_d is expressed as

$$t_d = Dirichlet(\mathbf{p}) \tag{4}$$

Where p denotes the K-dimensional hyperparameter vector and K denotes the predetermined number of topics. Assuming that the probability distribution of words in the document is also a Dilley distribution γ_k ,then for any topic its word probability distribution is denoted as:

$$\gamma_k = Dirichlet(\grave{e}) \tag{5}$$

where $\grave{e}$ denotes the V-dimensional hyperparameter vector and V denotes the total number of words in the dictionary.

For the nth word in any document d in the corpus, we obtain the distribution of the main and thematic counterparts w_{dn} by using a known thematic probability distribution o_{dn} model:

$$\begin{aligned} o_{dn} &= \prod t_d \\ w_{dn} &= \prod \gamma_{odn} \end{aligned} \tag{6}$$

3.3. *Word embedding representation based on language model*

The core idea of embedding is to map each word into a dense vector on a low latitude space, and to characterize the whole word by word vector. The word vector can reflect the cosine similarity between words with different meanings, and the cosine similarity between near-sense words should be larger. The generation of word embedding vectors depends on the constructed language model and a large text corpus, and this section focuses on two word embedding representations: word2vec and GloVe word embedding.

Word2vec represents a class of language models used to generate word vectors, which are shallow neural network models used to predict input words at adjacent positions and finally use the results of the hidden layer as word vectors. Nikolov et al. proposed two shallow word embedding models, skip-gram and continuous bag-of-words (The ContiWords, CBOW) models [19]. As shown in Figure 1, the CBOW model predicts the current word based on the context of multiple adjacent words, while the skip-gram model uses the current word to predict the adjacent words. The CBOW model takes a text sequence as a sample and uses the average of the contextual one-hot representations of the intermediate words as the input to the model, and then a hidden layer is used to perform the projection calculation. Suppose $W_{i-n+1}, ..., W_{i-1}, W_i$ represents a word sequence training sample, then the input of CBOW can be expressed as

$$x = \frac{1}{n-1} \sum_{w_j \in c} C w_j \tag{7}$$

Where n denotes the length of a sample word sequence and c denotes the set of contextual words.

The posterior probability of intermediate words can be predicted based on the contextual content of the intermediate words:

$$p(\ddot{w}c) = \frac{\exp c'(w)^T x}{\sum_{w' \in V} \exp c' w'^T x} \tag{8}$$

Where w represents the sample intermediate word, c denotes the context of the intermediate word, and w' denotes any word in the lexicon [21,22].

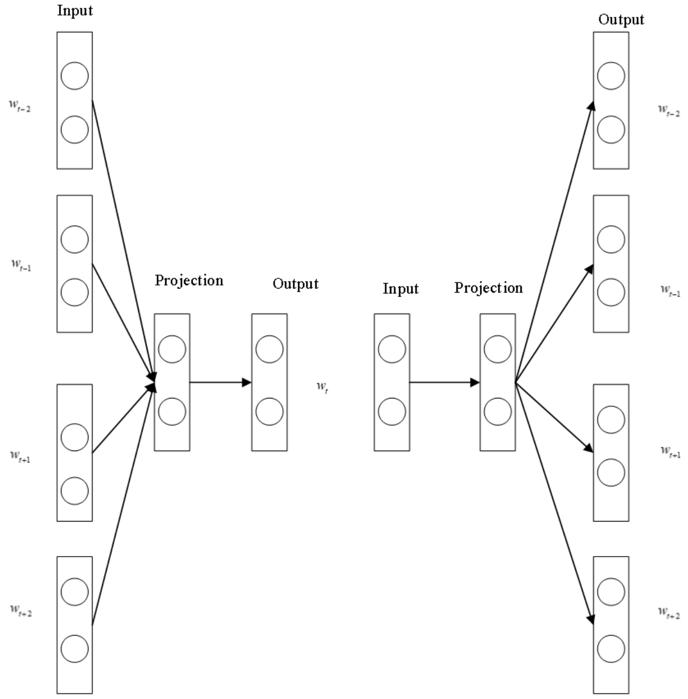

Figure 1. Two shallow word embedding models, left: CBOW; right: Skip-gram

The training strategy of the CBOW model is desired to maximize the posterior probability of predicting the intermediate words, i.e., to minimize the loss function of:

$$L(D) = \sum_{(w,c)\in D} \frac{1}{\log_2 p(\ddot{w})c} \tag{9}$$

Where (w,c) denotes a word sequence of length n, and D denotes the set of all possible word sequences in the corpus Skip- gram model is similar to CBOW model, except that it differs in input and output, which uses the same intermediate word to predict each word in the context, i.e., the one-hot representation of the intermediate word is used as the input of the model, and the one-hot representation of each word in the context is used as the output. The training strategy of Skij-gram is to maximize the posterior probability of the contextual words, and the loss function is expressed as follows:

$$L(D) = \sum_{(w,c)\in D} \sum_{w_j} \log p\ddot{w}w_j \tag{10}$$

$$p\ddot{w}w_j = \frac{\exp C'(w)^T C w_j}{\sum_{w^l \in V} \exp C' w' T C w_j} \tag{11}$$

Glove word embedding Although word2vec word embedding representation has made great progress in learning word-to-word relationships, it also has obvious disadvantages. word2vec uses a sliding window to take context, which leads to the fact that it can only use contextual information in a certain region, that is, it can only use local information and cannot take into account the global information of the whole corpus [23–25].

Suppose X denotes the co-occurrence matrix of word pairs in a corpus, and an element x_{ij}; denotes the number of occurrences of word j in word context,$\sum_k x_{ik}$ denotes the sum of occurrences of each word in the corpus in the word environment, then the co-occurrence probability of word j can be expressed as:

$$P_{ij} = P(\ddot{j}i) = \frac{x_{ij}}{\sum_k x_{ik}} \tag{12}$$

Similarly, the co-occurrence probability of simultaneous occurrence of word j when word k is used as the context is $P(\ddot{j}k)$. The co-occurrence probability ratio for three words involving i, j, k at the same time can be expressed as

$$R_{i,j,k} = P(\ddot{j}i)/P(\ddot{j}k) \tag{13}$$

4. Effects of positive and negative emotional feelings on teachers' emotional labor

As shown in Table 1 the teacher emotional feelings I and emotional labor correlation matrix.

	Deep behavior	Surface behavior	Natural behavior	Emotional labor perception	Total score of emotional labor
Positive sexual perception	0.341	-0.08	0.222	0.265	0.247
Negative feeling	-00.107	0.301	-0.023	-0.031	0.078

Table 1. Matrix of teachers' emotional feelings I in relation to emotional labor

Positive feelings were significantly positively correlated with deep behavior, natural behavior, emotional labor perception and total score negative feelings were significantly positively correlated with superficial behavior while the opposite trend appeared in the correlation status of positive feelings with superficial behavior and negative feelings with deep behavior as shown in Table 2.

	Deep behavior	Surface behavior	Natural behavior	Emotional labor perception	Total score of emotional labor
Extraversion	0.201	-0.51	-0.138	0.139	0.135
Nervous	-0.067	0.303	0.027	-0.18	0.11
Spirituality	-0.221	0.130	-0.057	-0.187	-0.117

Table 2. Matrix of correlations between teacher personality traits and emotional labor

Extraversion traits were significantly and positively correlated with deep behaviors, natural behaviors, emotional labor perceptions, and total emotional labor scores Neuroticism traits were only significantly and positively correlated with superficial behaviors and total scores Mentalities were significantly and negatively correlated with deep behaviors, clear labor perceptions, and total emotional labor scores while being positively correlated with superficial behaviors, as shown in Table 3.

	Deep behavior	Surface behavior	Natural behavior	Emotional labor perception	Total score of emotional labor
Average	3.85	3.42	3.78	4.01	129.57
Standard deviation	0.44	0.55	0.62	0.41	11.89

Table 3. General overview of teachers' emotional labor

Figure 2 shows that teachers' total emotional labor scores are approximately normally distributed, with a skewness of 0.229, indicating that the long tail of the distribution curve is to the right, slightly skewed to the right. Among the scores of each dimension, emotional labor perception topped the list, followed by deep behavior, then natural behavior, while superficial behavior had the lowest score [26–28].

4.1. Differences in teachers' emotional labor in school-level dimensions

The results of the one-way ANOVA for teachers' emotional labor in the school level dimension are shown in Table 4 below.

Figure 3 The scores of the dimensions of emotional labor differed significantly between schools at different levels. Post hoc comparisons showed that for deep behaviors, natural behaviors and emotional labor perceptions, the municipal focus schools outperformed the provincial schools; for superficial behaviors, on the other hand, the municipal focus schools were significantly lower than the provincial and other categories of schools.

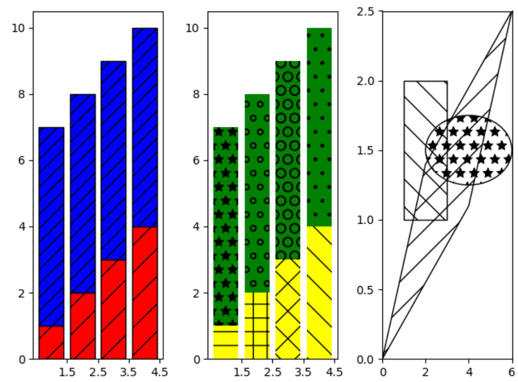

Figure 2. Histogram of frequency distribution of total teacher emotional labor scores

Dependent variable	F value	Post comparison
Deep behavior	5.19	Provincial level <municipal level key**
Surface behavior	3.08	Provincial and municipal key*
Natural behavior	4.24	Key at municipal level >provincial level * *, others*
Emotional labor perception	3.31	Provincial and municipal key*

Table 4. One-way ANOVA results for teachers' emotional labor in the school level dimension

4.2. Differences in teachers' emotional labor in the grade level of teaching dimension

As shown in Table 5 the results of the one-way ANOVA for teachers' emotional labor in the grade level of teaching dimension.

Figure 4 The total emotional labor score and its dimensional scores differed at significant levels in the grade dimension. Elementary school teachers scored significantly higher than secondary school teachers.

5. Conclusions

In this paper, based on the optimization and management of artificial intelligence English teachers' emotional labor, the data from both predicted and formally administered tests were combined for the corresponding statistical analysis. Yes, individual college English teachers are working on emotional regulation for non-personal issues, temporarily restraining anger and cursing impulses, and communicating with students in a pleasant manner.

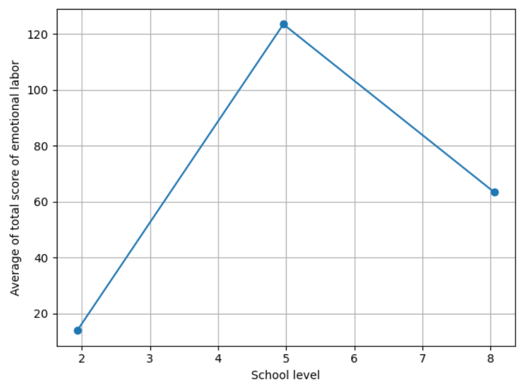

Figure 3. Average of the total emotional labor scores of instructors at different school levels

Dependent variable	F value	Post comparison
Deep behavior	4.68	Primary school, junior high school and senior high school*
Surface behavior	5.52	Primary school >junior high school*
Natural behavior	4.20	Primary school >High School*
Emotional labor perception	7.33	Primary school >High School**
Total score of emotional labor	7.52	Primary school >junior high school * *, senior high school*

Table 5. One-way ANOVA results for teachers' emotional labor in the grade level of teaching dimension

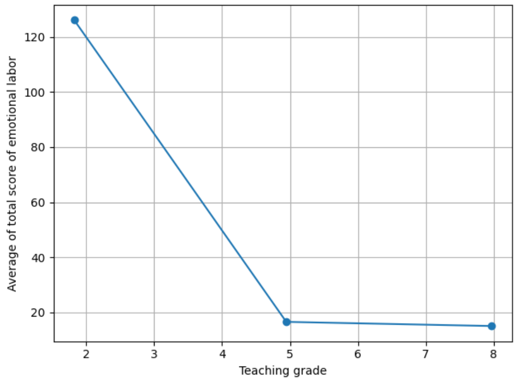

Figure 4. Mean of total emotional labor scores of teachers in different grades

Data Availability

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

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References

1. Perrotta, C., Selwyn, N. and Ewin, C., 2022. Artificial intelligence and the affective labour of understanding: The intimate moderation of a language model. *New Media & Society*, p.14614448221075296.

2. Yunjie, J., 2021. Research on the practice of college English classroom teaching based on Internet and artificial intelligence. *Journal of Intelligent & Fuzzy Systems*, (Preprint), pp.1-10.

3. Ning, W., 2016. A study of English intelligent classroom model based on artificial intelligence and emotion judgment. *Revista Iberica de Sistemas e Tecnologias de Informacao*, (18B), p.105.

4. Lu, Y., 2019. Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of Management Analytics, 6*(1), pp.1-29.

5. Duan, W., Gu, J., Wen, M., Zhang, G., Ji, Y. and Mumtaz, S., 2020. Emerging technologies for 5G-IoV networks: applications, trends and opportunities. *IEEE Network, 34*(5), pp.283-289.

6. Moreno-Guerrero, A.J., Lopez-Belmonte, J., Marin-Marin, J.A. and Soler-Costa, R., 2020. Scientific development of educational artificial intelligence in Web of Science. *Future Internet, 12*(8), p.124.

7. Zhang, J., 2021. Reform and innovation of artificial intelligence technology for information service in university physical education. *Journal of Intelligent & Fuzzy Systems, 40*(2), pp.3325-3335.

8. An, P., Wang, Z. and Zhang, C., 2022. Ensemble unsupervised autoencoders and Gaussian mixture model for cyberattack detection. *Information Processing & Management, 59*(2), p.102844.

9. Williamson, B., 2017. Moulding student emotions through computational psychology: Affective learning technologies and algorithmic governance. *Educational Media International, 54*(4), pp.267-288.

10. Farouk, A. and Zhen, D., 2019. Big data analysis techniques for intelligent systems. *Journal of Intelligent & Fuzzy Systems, 37*(3), pp.3067-3071.

11. Di Vaio, A., Palladino, R., Hassan, R. and Escobar, O., 2020. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research, 121,* pp.283-314.

12. Cao, Y., 2021, May. Innovation and reform of accounting professional training model based on the artificial intelligence. *In Journal of Physics: Conference Series* (Vol. 1915, No. 4, p. 042023). IOP Publishing.

13. Saghezchi, F.B., Radwan, A., Rodriguez, J. and Dagiuklas, T., 2013. Coalition formation game toward green mobile terminals in heterogeneous wireless networks. *IEEE Wireless Communications, 20*(5), pp.85-91.

14. Lee, H.S. and Lee, J., 2021. Applying artificial intelligence in physical education and future perspectives. *Sustainability, 13*(1), p.351.

15. Rajendran, S., Khalaf, O.I., Alotaibi, Y. and Alghamdi, S., 2021. MapReduce-based big data classification model using feature subset selection and hyperparameter tuned deep belief network. *Scientific Reports, 11*(1), p.24138.

16. Khalaf, O.I. and Abdulsahib, G.M., 2021. Design and Performance Analysis of Wireless IPv6 for Data Exchange. *Journal of Information Science & Engineering, 37*(6).

17. Grewal, D.S., 2014. A critical conceptual analysis of definitions of artificial intelligence as applicable to computer engineering. *IOSR Journal of Computer Engineering, 16*(2), pp.9-13.

18. Huang, J., Saleh, S. and Liu, Y., 2021. A review on artificial intelligence in education. *Academic Journal of Interdisciplinary Studies, 10*(206).

19. Quan, Y., 2020. Development of computer aided classroom teaching system based on machine learning prediction and artificial intelligence KNN algorithm. *Journal of Intelligent & Fuzzy Systems, 39*(2), pp.1879-1890.

20. Lin, S., Dongul, E.S., Uygun, S.V., Ozturk, M.B., Huy, D.T.N. and Tuan, P.V., 2022. Exploring the relationship between abusive management, self-efficacy and organizational performance in the context of human-machine interaction technology and artificial intelligence with the effect of ergonomics. *Sustainability, 14*(4), p.1949.

21. Huang, J., Shen, G. and Ren, X., 2021. Connotation analysis and paradigm shift of teaching design under artificial intelligence technology. *International Journal of Emerging Technologies in Learning (iJET), 16*(5), pp.73-86.

22. Gardner, J., O'Leary, M. and Yuan, L., 2021. Artificial intelligence in educational assessment:'Breakthrough? Or buncombe and ballyhoo?'. *Journal of Computer Assisted Learning, 37*(5), pp.1207-1216.

23. Ali, R., Afzal, M., Sadiq, M., Hussain, M., Ali, T., Lee, S. and Khattak, A.M., 2018. Knowledge-based reasoning and recommendation framework for intelligent decision making. *Expert Systems, 35*(2), p.e12242.

24. Ali, R., Khatak, A.M., Chow, F. and Lee, S., 2018, January. A case-based meta-learning and reasoning framework for classifiers selection. *In Proceedings of the 12th international conference on ubiquitous information management and communication* (pp. 1-6).

25. Hu, J., Liu, B. and Peng, H., 2021. Role of AI for application of marketing teaching-A research perspective. *Journal of Intelligent & Fuzzy Systems, 40*(2), pp.3711-3719.

26. Oh, C., Lee, T., Kim, Y., Park, S., Kwon, S. and Suh, B., 2017, May. Us vs. them: Understanding artificial intelligence technophobia over the google deepmind challenge match. *In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (pp. 2523-2534).

27. Kumar, V., Rajan, B., Venkatesan, R. and Lecinski, J., 2019. Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), pp.135-155.

28. Zhang, Q. and Ji, Z., 2022. Research on the hierarchical teaching method of university English based on artificial intelligence wireless network. *Wireless Communications and Mobile Computing, 2022.*