



FLEXIBLE ENGLISH LEARNING PLATFORM USING COLLABORATIVE CLOUD-FOG-EDGE NETWORKING

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Abstract. In the modern age, developing practical online learning tools for English language learners is challenging due to existing systems' shortcomings. These systems often need proper instructional design, are well-connected to motivational theories, and have limited infrastructure for data sharing, leading to poor learning outcomes and low motivation. To tackle these issues, a new approach called OAELT has been proposed in this paper. OAELT is an Online Assisted English Learning Tool that uses the Fuzzy Analytical Hierarchy Process (FAHP) and collaborative cloud-fog-edge networking to create a flexible learning design that adapts to the needs and preferences of individual learners. Using the FAHP approach, OAELT provides an improved learning experience by tailoring its design to each learner's unique needs. The collaborative cloud-fog-edge networking approach uses each computing layer's strengths to deliver a personalized and seamless learning experience. OAELT employs adaptive and dynamic approaches within a flexible instructional paradigm to ensure effective instructional design. This paradigm facilitates collective learning data exchange across cloud, fog, and edge computing layers. The effectiveness of OAELT was evaluated using a descriptive statistics approach, which included a five-dimension questionnaire for students covering cognition, emotion, action, cooperation, and literacy. The results demonstrated that OAELT could enhance learning effectiveness and motivation while providing a flexible and seamless learning experience. According to the experimental data of the proposed model, 46.8% of learners often read English magazines and newspapers to improve their flexibility in English learning. Additionally, 50.4% classified and memorized English according to their categories, while 59% of learners often used context to memorize. These findings suggest that the traditional methods for flexible English learning are not adequate, and the average score of the student's methods and strategies is mediocre. However, after using OAELT, some students have been able to use different learning curricular reading. Overall, OAELT's integration of cloud-fog-edge computing with a flexible English learning design can create a more effective and personalized learning system that addresses the challenges of modern learning.

Key words: Fuzzy AHP, Cloud-fog-edge collaboration, collaborative interaction, cooperative networks, e-learning, m-grammar learning, adaptive language learning, motivation model, student learning experience.

1. Introduction. The demand for effective and efficient learning tools for English language learners has been on the rise in recent years [16]. Traditional language learning approaches have struggled to keep up with modern technologies, resulting in inadequate learning outcomes. To address this issue, modern tools and approaches need to be incorporated to enhance the instructional design and learning process. Self-directed learning and online-assisted language learning tools have become increasingly popular, as they provide learners with independent learning opportunities. Although online-assisted language learning tools have been introduced to develop various language skills, including grammar [16, 12], there are concerns about the effectiveness of existing systems due to a lack of theoretical reference, motivation, and poor instructional design. An adaptive and dynamic approach that caters to learners' needs, as illustrated in Fig 3.1 [16], is required to address these concerns.

The adaptability of the learning system refers to its ability to evaluate learners' actions and guide them in the study process, while the dynamic part refers to the system's flexibility to change its structure according to the demands of the students. However, existing online-assisted English learning applications cannot fully ensure both the adaptive and dynamic attributes of learning, and they have little consideration for motivational factor and cognitive load management [12]. Therefore, there is a need to investigate potential solutions to address these concerns and enhance the effectiveness of online-assisted English learning tools.

Existing instructional tools often suffer from a common problem of providing the same learning materials to all learners, regardless of their proficiency level. Such an approach fails to consider the unique learning

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characteristics of individual learners, and can lead to boredom or underestimation of the learning material, ultimately resulting in an increased cognitive load. To address this limitation, we propose an adaptive and dynamic learning system, named the Online-Assisted English Learning Tool (OAELT), which takes into account the evolving learning characteristics, motivation, cooperation, and learning performance of individual students. The aim of the system is to enhance the functionality of existing learning tools by incorporating adaptive and dynamic learning attributes, building upon the networking-assisted learning system that has been previously studied. The ultimate goal is to develop a flexible English learning system that can effectively cater to the individual learning needs of each student.

The proposed Online Assisted English Learning Tool (OAELT) system was designed to provide users a seamless and personalized learning experience. This was achieved by incorporating a flexible English learning design using Fuzzy Analytical Hierarchy Process (FAHP) with collaborative cloud-fog-edge computing. The FAHP approach allowed for a learning design that could adapt to the individual needs and preferences of the learner [14], resulting in a better learning experience. Collaborative cloud-fog-edge networking also played a significant role in the platform's success, leveraging the strengths of each computing layer to provide a seamless and personalized learning experience. The cloud layer provided centralized infrastructure, while the fog and edge layers distributed computing resources closer to the user, enabling faster response times and offline learning experiences [16, 14]. The purpose of this study was to investigate the potential of the proposed OAELT system as a solution to the challenges in English language learning and to demonstrate its effectiveness through quantitative research and collaborative network performance evaluation.

Integrating Fuzzy Analytical Hierarchy Process (FAHP) with collaborative cloud-fog-edge networking has transformed the Online Assisted English Learning Tool (OAELT) system into a more effective, personalized learning solution. This new approach overcomes the challenges of modern learning, providing users with a flexible and seamless learning experience. The system was evaluated using descriptive statistics from a five-dimension questionnaire for students, which assesses cognition, emotion, action, cooperation, and literacy. The evaluation demonstrated that OAELT successfully enhanced learning effectiveness and motivation, making it a promising solution for Online Assisted English Learning.

The main contributions of the paper are as follows:

1. Proposed a novel approach to the Online Assisted English Learning Tool (OAELT) that incorporates a flexible English learning design using Fuzzy Analytical Hierarchy Process (FAHP) and collaborative cloud-fog-edge networking.
2. The proposed OAELT system uses machine learning algorithms to personalize the learning experience, catering to each learner's unique needs and preferences. Customized learning materials and game elements are incorporated to increase learner motivation and engagement.
3. The proposed OAELT system has been shown to be effective in improving its users' learning outcomes and motivation. This was evaluated using a five-dimension questionnaire for students that covers cognition, emotion, action, cooperation, and literacy.
4. The evaluation provides descriptive statistics demonstrating the system's ability to enhance learning effectiveness and motivation while providing a flexible and seamless learning experience.

2. Literature Review. Recent research has mainly focused on developing flexible English learning platforms to meet the growing demand for such platforms due to accessibility, convenience, personalization, technological advances, and globalization. However, common limitations in online English language learning have been identified, including a lack of human interaction, limited feedback, motivation, and quality control. Researchers are exploring new technologies and instructional methods such as chatbots, virtual reality, and gamification to address these challenges to provide more interactive and engaging learning experiences. Moreover, efforts are being made to incorporate more opportunities for human interaction and feedback into online learning platforms through features such as video conferencing and live chat with tutors. Additionally, accreditation and quality control measures are being implemented to ensure the quality of online learning content and instruction. Below are some of the studies that are relevant to our work:

According to papers [17, 16] the existing English language learning systems have not been very effective due to three key reasons: firstly, they are not designed based on motivational theoretical principles; secondly, the instructional design is not proper; and thirdly, there is a lack of proper infrastructure for data sharing

between students and instructors. To address these issues, this paper proposes MATT: a Mobile-Assisted Tense Tool that uses an m-grammar instructional design and leverages cloud-fog-edge collaborative networking. The Cognitive Theory of Multimedia Learning principles is integrated into MATT to minimize cognitive load, and a motivational model is incorporated to increase motivation and learning effectiveness. To ensure effective instructional design, the system uses adaptive and dynamic approaches through a flexible instructional paradigm that enables cooperative learning data exchange across the cloud (central unit), fog (regional units), and edge (end devices/learners). Merely utilizing the collaborative cloud-fog-edge technique falls short of meeting these demands, the paper [1] focuses on the security and privacy challenges associated with fog and edge computing. The authors survey the main challenges and explain how these issues can impact the implementation of fog and edge computing. Furthermore, the paper presents various countermeasures to address and mitigate the potential impact of these security challenges.

The author [6] focuses on the controversial nature of human factors constructs and the widespread use of the NASA-TLX (Task Load Index) measurement tool. The author provides a critical perspective on the use of the NASA-TLX, a widely-used tool for measuring perceived mental workload, and highlights some of the challenges and limitations associated with this measure. The paper emphasizes the importance of carefully considering human factors constructs' theoretical foundations and measurement properties and associated measurement tools.

In article [3], the author proposes this article to address the challenges associated with transmitting large amounts of data between edge and cloud computing systems in predictive maintenance (PM) applications. The article discusses the use of federated learning (FL) as a mechanism that allows the creation of a model from distributed data across edge, fog, and cloud layers without violating privacy. However, FL faces challenges in asset management, particularly in PM applications. The article proposes two federated algorithms, Federated Support Vector Machine (FedSVM) and Federated Long-Short Term Memory (FedLSTM) [18], for PM applications, which allow factories at the fog level to maximize the accuracy of their PM models without compromising privacy. The proposed algorithms aim to enable collaborative PM applications that are efficient, accurate, and secure.

This article [19] explores the use of three-dimensional reconstruction of medical images and virtual reality (VR) technology in nursing experiment teaching. The goal is to provide an easier and more effective learning experience for students and simplify teachers' teaching process by incorporating VR technology. The article proposes using VR application technology to create an immersive learning environment that can enhance student understanding and engagement.

Ultimately, the aim is to improve the quality of nursing education through the integration of advanced technologies, [15] suggests that to improve the quality of distance learning, it is important to provide more interactive and diverse content that incorporates multimedia elements like text, images, animations, sounds, and videos. The author proposes a web-based application that combines interactive multimedia and a game-based approach to support distance learning. The aim is to make the learning experience more engaging and enjoyable for students and to provide a more effective way of delivering educational content to learners who are not physically present in a classroom. By using interactive multimedia and a game-based approach, the proposed application could potentially enhance learners' motivation and learning outcomes. The article [17] explains that current systems for teaching grammar often fail to engage and motivate students, which can lead to a higher cognitive load and poorer learning outcomes. To address these issues, the paper proposes a new approach that uses smart communication networks to manage cognitive load and improve the learning experience. By focusing on pedagogically informed instructional design, the proposed system aims to balance the cognitive load better and increase engagement, resulting in better learning outcomes.

Article [7] describes the increasing demand for data processing and optimization due to the billions of data bytes generated at the network edge. As a solution to this challenge, the article proposes the integration of edge computing and artificial intelligence, which is referred to as edge intelligence [8] This work discusses the issue of latency in the communications and processing procedures in a fog network caused by the workload imbalance among IoT devices and base stations (BSs). To address this problem, the author proposes a workload balancing scheme to minimize latency by assigning IoT devices to suitable BSs. This scheme ensures that the workload is distributed evenly among the BSs, which optimizes the processing and communications procedures

and minimizes latency [2]. This article discusses how to manage the large amounts of data generated by IoT devices and process it effectively. The proposed solution is to use cloud computing to store and process the data, and IoT can help manage tasks offloaded to the cloud. The article also emphasizes improving application performance by measuring power utilization, makespan, and execution time. The proposed model uses fog computing to decrease processing time, and its effectiveness is compared to other existing systems.

The article [4] describes a course on autonomous aerial robotics available in the Robotics Academy framework. The study, which is free and open-access, teaches students how to program drones without the need for a physical drone. Students can use their computers to program various types of drones [5] This article reviews 134 research studies on online teaching and learning practices in teacher education. The author identified different practices related to social, cognitive, and teaching presence in online education. These practices are important for ensuring effective online teaching and learning experiences for teachers and students, [9] explains that online learning experiences, which are carefully designed and planned, are distinct from courses offered online in response to a crisis or disaster. Due to the COVID-19 pandemic, many colleges and universities have had to resort to emergency remote teaching to maintain instruction. However, the article emphasizes that this emergency remote teaching should not be equivalent to well-planned online learning experiences. The report highlights the importance of understanding these differences to evaluate the effectiveness of emergency remote teaching during the COVID-19 pandemic.

Article [7] discuss a professional development (PD) program designed for teachers to introduce them to the maker movement and its principles. The goal was to help teachers integrate maker-centered learning into their curriculum. The purpose of this article [11] is to introduce a platform called PaPL, which stands for Paper-based Programming Languages. The report suggests that using paper as a means of interaction is a low-cost and flexible solution that can take advantage of the prevalence of paper in classrooms. The authors aim to make the platform easy to reproduce and accessible for anyone interested in introducing paper-based programming languages in their teaching or learning activities.

Existing online-assisted language learning tools typically follow a pre-designed course structure, which means that learners progress through the content in a linear manner regardless of their individual needs or abilities. This approach can be limiting because learners may not receive the support they need to overcome specific challenges or advance at their own pace. In contrast, OAELT utilizes an adaptive approach that tailors the learning experience to the individual learner's needs and abilities. This is achieved through the use of machine learning algorithms that analyze learner performance and provide personalized feedback and recommendations for further study. Additionally, OAELT's dynamic approach allows for real-time adjustments to the learning experience, enabling learners to receive immediate support when they encounter difficulties or need additional guidance.

By incorporating adaptive and dynamic features, OAELT addresses the limitations of traditional online-assisted language learning tools. It provides learners with a more personalized and responsive learning experience, enabling them to progress at their own pace and receive the support they need to overcome specific challenges. This approach can result in increased engagement, motivation, and ultimately, improved language learning outcomes.

Thus, the above work discusses the advantages and disadvantages of existing teaching modes and how research techniques can be used to create a flexible English learning platform using modern efficient techniques, which will be described below.

3. OAELT System Model. The OAELT system model assumes that its components are deployed in the users' devices such as mobile phones, tablets, and laptops. These devices are used to access the system, and the data collected from them is processed using two layers - Fuzzy AHP and Fuzzy Logic.

The Fuzzy AHP (Analytic Hierarchy Process) layer is used to determine the priorities and weights of the different learning elements or parameters. This layer is designed to address the limitations of the traditional AHP method, which assumes that the decision-making criteria are crisp and precise. In contrast, the Fuzzy AHP considers the uncertainty and vagueness associated with decision-making criteria and assigns fuzzy weights to them. This helps in creating a more accurate and flexible decision-making framework.

The Fuzzy Logic layer is used to analyze the collected data and provide personalized recommendations to the learners. This layer uses fuzzy set theory to handle imprecision and uncertainty associated with linguistic

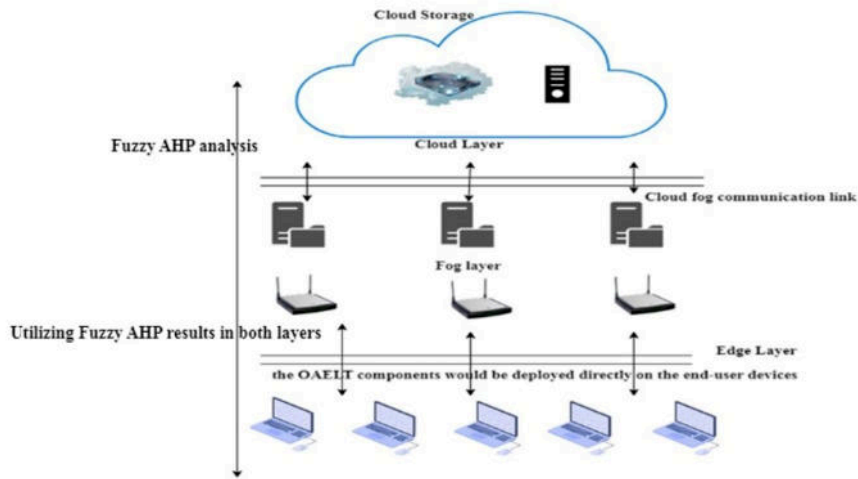


Fig. 3.1: OAELT architecture

variables. It helps in providing learners with more personalized learning experiences based on their individual needs and preferences.

The system also utilizes fog, edge, and cloud layers to control communications between the different components of the system. The fog and edge layers are used to provide early access to the learning contents, which helps in reducing the latency and improving the overall performance of the system. The cloud layer is used to store and process large amounts of data and to provide on-demand access to the learning materials

3.1. FAHP and Collaborative Cloud-Fog-Edge Methodologies. In this section, we discussed two methods 1. FAHP (Fuzzy Analytical Hierarchy Process 2. Collaborative Cloud-Fog-Edge networking.

3.2. FAHP. The Fuzzy Analytical Hierarchy Process (FAHP) is a decision-making methodology that combines fuzzy set theory and the extension principle to provide more accurate results than traditional AHP [14, 13]. The FAHP approach is advantageous when decision-makers are uncertain or vague in their judgments, as it can reduce or remove errors resulting from biases or vagueness.

1. Fuzzy set theory

Fuzzy set theory is a mathematical framework that allows for representing uncertainty and vagueness in decision-making by introducing degrees of membership between 0 and 1. The extension principle is a mathematical principle that calculates the degree of an element's membership in a set. It extends the concept of a function from a subset of a domain to the entire field. In FAHP, fuzzy set theory and the extension principle are applied to the AHP method to enhance its accuracy in decision-making. This section of the paper explains how the FAHP approach uses fuzzy set theory and the extension principle to achieve more reliable decision-making outcomes.

A set of fuzzy numbers can assist decision-making processes, either in triangular form (a, b, c) or interval-valued trapezoidal form (a, b, c, d). Fuzzy numbers represent values that are uncertain or vague and are not easily quantifiable using traditional mathematical methods. In triangular form, a fuzzy number is characterized by three values: the minimum value (a), the most probable value (b), and the maximum value (c). In interval-valued trapezoidal form, a fuzzy number is defined by four values: the left endpoint (a), the left shoulder (b), the right shoulder (c), and the right endpoint (d). These fuzzy numbers are useful in expressing the subjective judgments of decision-makers and enable the integration of imprecision and uncertainty in decision-making procedures [13].

Provides arithmetic operations between two triangular Fuzzy numbers (TFN) [13]. Consider two positives m_1 and m_2 as (a_1, b_1, c_1) and (a_2, b_2, c_2) respectively. Fuzzy summation and fuzzy subtraction of two fuzzy

numbers are represented as \ominus and \oplus .

Assume that

$$\widetilde{m}_1 \oplus \widetilde{m}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{3.1}$$

$$\widetilde{m}_1 \ominus \widetilde{m}_2 = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \tag{3.2}$$

$$\widetilde{m}_1 \otimes \widetilde{m}_2 = (a_1 a_2, b_1 b_2, c_1 c_2) \tag{3.3}$$

$$\lambda \otimes \widetilde{m}_1 = \lambda a_1, \lambda b_1, \lambda c_1 \tag{3.4}$$

where $\lambda > 0, \lambda \in R$

$$\widetilde{m}_1^{-1} = \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1} \right) \tag{3.5}$$

The application of extent analysis principles in comparing two sets of triangular fuzzy numbers (TFNs) [13].

In this context, the objective set is represented by TFNs with membership values given by $x = \{x_1, x_2, \dots, x_n\}$ and the goal set is represented by TFNs with membership values given by $u = \{u_1, u_2, \dots, u_n\}$ respectively. To apply extent analysis principles, deriving each object from the sets and performing extent analysis for each goal. This means that for each goal, the degree of membership of each object is evaluated using extent analysis.

m extent analysis values can be derived for each object, where m represents the number of goals being considered. The values are represented by the formula:

$$m_{g_i}^1, m_{g_i}^1 \dots m_{g_i}^m, \quad i = 1, 2, \dots, n \tag{3.6}$$

In this formula, $m_{g_i}^j (j = 1, 2 \dots n)$ represents $a, ,$ Chang’s extent analysis procedure adopted for fuzzy AHP as follows.

Algorithm 1: Fuzzy AHP analysis

Step 1: Obtain the hierarchy structure:

The process of breaking down a problem into smaller parts to make it easier to solve. In this case, the problem is about prioritizing things that are barriers to learning English, and an expert in the field is consulted to help identify the main barriers. Once the barriers are identified, they are organized into a hierarchy, with the most important ones at the top. Then, the barriers are broken down into even smaller parts that need to be considered when prioritizing them. By doing this, it becomes easier to understand and solve the problem effectively.

Step 2: Obtain the pairwise comparison:

Compare the importance of different barriers in English learning, and this can be done by an expert’s opinion. To compare these barriers, experts need to use triangular fuzzy numbers (TFNs) which help to represent the range of possible values for a given parameter. The TFNs have three values, a lower bound, a midpoint, and an upper bound, which represent the expert’s best estimate, range of uncertainty, and imprecision around that estimate. Experts can use TFNs to determine the relationship between two barriers in terms of their relative importance.

Step 3: Evaluation of Fuzzy scores:

$$FS_i = \sum_{i=1}^m m_{g_i}^j \varphi \left[\sum_{i=1}^n \sum_{j=1}^m m_{g_i}^j \right]^{-1} \tag{3.7}$$

Using Fuzzy summation of TFN m extent analysis values $\sum_{j=1}^m m_{gi}^j$ obtained as

$$\sum_{j=1}^m m_{gi}^j = \left(\sum_{j=1}^m a_j, \sum_{j=1}^m b_j, \sum_{j=1}^m c_j \right) \tag{3.8}$$

And $[\sum_{i=1}^n \sum_{j=1}^m m_{gi}^j]^{-1}$ summation of fuzzy $m_{gi}^j (j = 1, 2, \dots, m)$ values performed to get

$$\sum_m^n \sum_n^m m_{gi}^j = \left(\sum_{i=1}^n a_j, \sum_{i=1}^n b_j, \sum_{i=1}^n c_j \right) \tag{3.9}$$

Inverse vector may be derived as

$$\left[\sum_{i=1}^n \sum_{j=1}^m m_{gi}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^n c_j}, \frac{1}{\sum_{i=1}^n b_j}, \frac{1}{\sum_{i=1}^n a_j} \right) \tag{3.10}$$

Step 4: Obtain the degree of possibility of supremacy

$$m_2 = (a_1, b_1, c_1) \geq m_1 = (a_1, b_1, c_1)$$

$$v = (m_2 \geq m_1) = \sup[\min(\mu_{m_1}(x), (\mu_{m_2}(y)))] \tag{3.11}$$

Expressed equivalently

$$v = (m_2 \geq m_1) = ht(m_1 \cap m_2) = \mu_{m_2}(d) \tag{3.12}$$

$$\mu_{m_2}(d) = \begin{cases} 1 \\ 0 \\ \frac{a_1 - c_2}{(b_2 - c_2) - (b_2 - c_2)} \text{ if } b_2 \geq b_1, \text{ if } a_1 \geq c_2 \end{cases} \tag{3.13}$$

Step 5: Obtain the degree of possibility for a given convex fuzzy number it is greater than K convex Fuzzy number $m_1 (i = 1, 2, \dots, k)$ defined as

$$v = (m \geq m_1, m_2 \dots \dots m_K) = v[(m \geq m_1) \text{ and } m \geq m_2 \text{ and } \dots \dots (m \geq m_K)] \tag{3.14}$$

$$= \min v(m \geq m_i), i = 1, 2 \dots \dots K$$

Considering

$$d(a_i) = \min v(s_i \geq s_K) \text{ for } K = 1, 2, \dots \dots m; K \neq i \tag{3.15}$$

Weight vector derived as $w = (d(a_1), d(a_2), \dots \dots, d(a_n))^T$ such that $a_i (i = 1, 2 \dots \dots, n)$ has n elements

Step 6: Obtain the normalized weight vectors:

$$w = (d(a_1), d(a_2), \dots \dots, d(a_n))^T \tag{3.16}$$

Where W denotes the non-fuzzy number

Step 7: Compute the overall score

To determine the overall importance of barrier dimensions and factors, priority weightage is calculated using both local weightage and global weightage. Global weightage measures the importance of each barrier dimension or factor across all dimensions and factors, while local weightage measures importance within each group. To obtain the overall score, the global weightages are arranged in descending order for the respective prioritization. This allows for the identification of the most important barrier dimensions and factors, which can then be addressed in order to improve e-learning outcomes.

3.3. Collaborative Cloud-Fog-Edge (CCFE). Collaborative Cloud-Fog-Edge (CCFE) networking is an innovative approach to distributed computing that leverages the strengths of cloud computing, fog computing, and edge computing resources to deliver more efficient and flexible services to end-users. This methodology relies on the collaboration between cloud servers, fog servers, and edge devices to provide computing resources, storage, and processing capabilities to end-users which shows in Fig 3.1. Cloud computing, which utilizes remote servers in large data centers, is effective for managing large data volumes and handling complex processing tasks. Meanwhile, fog computing employs intermediate computing nodes positioned closer to the end-users to reduce latency and enhance the response time of services that require real-time processing. Edge computing utilizes local computing resources, such as smartphones, tablets, and IoT devices, to provide localized processing and storage capabilities, and reduce the amount of data transmitted over the network. By combining these diverse computing resources, CCFE networking optimizes computing resources to provide cost-effective services. CCFE networking has various applications, including IoT, big data processing, multimedia services, and flexible and adaptive learning environments in education. By integrating cloud, fog, and edge computing resources, CCFE networking enhances the user experience by providing a more seamless and efficient service delivery, thereby improving the overall quality of service.

In OAELT model the CCFE networking approach provides several advantages to a Flexible English Learning Platform in delivering a more seamless and efficient service. Firstly, it offers cost-effective computing resources for learners by utilizing cloud servers for data management, and fog servers and edge devices for processing and storage. This allows the platform to handle large amounts of data and complex tasks more efficiently, making it possible for learners to access the platform from anywhere using any device, thereby improving their learning experience. Secondly, CCFE networking improves the platform's response time and reduces latency. Intermediate computing nodes can be located closer to learners with fog computing, resulting in faster data processing and better response time. This is particularly beneficial for features such as real-time assessments, where timely feedback is critical for learner progress. Finally, the CCFE approach allows for personalized and adaptive learning experiences. Edge computing provides localized processing and storage capabilities, enabling the platform to collect and analyze data about each learner's preferences, strengths, and weaknesses. Based on this analysis, the platform can tailor learning experiences to each learner, offering customized learning paths, recommendations, and assessments.

Algorithm 2: Fog-edge- cloud communication

Step 1: Cloud server executes
Step 2: Initialize w_0
Step 3: for each round $t = 0, 1, \dots, t_g$ do
 for each factory site $J \in m$ do
 $w_{fog,J}^{t+1} \leftarrow fog\ server\ executes(J, w_{cloud}^t)$
 end
 $w_{cloud}^t \leftarrow \sum_{J=1}^m a_J w_{fog,J}^{t+1}$
end
Step 4: Fog server executes (J, w_{fog}) :
 $h_J \leftarrow stepsize$
 for each round $t = 0, 1, \dots, t_l^J$ do
 for each edge device $i \in n$ do
 $w_{i,J}^{t+1} \leftarrow edge\ device\ update(i, w_{fog}^t)$
 end
 $w_{fog,J}^{t+1} \leftarrow \sum_{i=1}^{n_J} \frac{d_i^J}{d^J} w_{i,J}^{t+1}$
 end
Step 5: $w_{fog,J}^{t+1}$ will be return to the cloud server by request
Step 6: Edge device update (J, i, w) :
 $\{d_i\}_{i=1}^n = data\ partition$
 for each local epoch k from 1 to E do
 $w_{i,J}^{t+1} = w_{i,J}^t - \eta \nabla f_i^J(w_{i,J}^t)$

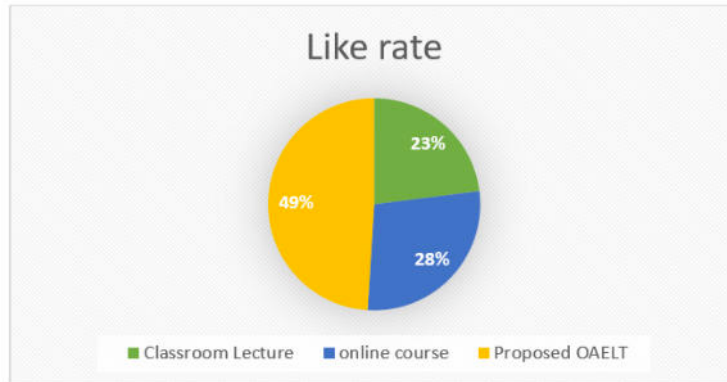


Fig. 4.1: Favourite Learning mode

end

Return $w_{i,J}$ to j th fog server

$f_i^J(w_{i,J}^t)$ denotes the loss function for predicting the correctness of the student's English response. We can train the model collaboratively using the cloud, fog, and edge devices to improve the prediction accuracy while minimizing the communication overhead. The partitioned data can be the students' responses and related metadata, such as their English proficiency level, age, and learning history.

4. Results and experiments.

4.1. Dataset. Based on the study described in [10], our proposed model involved an experimental setup that included a SPOC course offered on the MOOC platform of Chinese universities. The study was conducted with a total of 120 participants, including 1 lecturer, 1 postgraduate assistant, and 120 students. The students were from two classes of the same grade at Sichuan Normal University and were divided into an experimental group and a control group, each consisting of 60 students. During the preparation stage of the experiment, 120 questionnaires were distributed to investigate the participants' attitude towards online learning, online learning experience, and willingness to serve as a scholar. All 120 questionnaires were completed and returned, and were considered valid for analysis. Favourite mode of learning is shown in Figure 4.1.

Based on the questionnaire results presented in Figure 4.1, it is evident that a significant proportion of students in the experimental group (49%) preferred a learning mode that combined course teaching with online learning. This finding indicates that the majority of students preferred a blended learning model that integrates both traditional classroom teaching and online learning, rather than a single learning model. This suggests that there is a growing demand for a teaching model that combines the benefits of both traditional and online learning methods. In response to this demand, the development of SPOC (Small Private Online Course) courses was initiated. These courses aim to leverage the benefits of both traditional classroom teaching and online learning, providing students with a flexible and personalized learning experience. With the help of the OAELT online assisted English learning tool, which incorporates techniques such as Fuzzy AHP and collaborative cloud-fog-edge networking, SPOC courses can be tailored to suit the individual learning needs of each student. The platform provides a collaborative and interactive learning environment, where students can engage with course materials and peers, at any time and from any location.

In this section, we developed a questionnaire to investigate the cognitive state, emotional state, motor skills, interaction and cooperation, and information technology literacy of the students in both the experimental and control groups, in line with the goals and evaluation system of the OAELT model that incorporates Fuzzy AHP and collaborative cloud-fog-edge networking. The questionnaire was distributed to the students prior to the experiment, and the collected data was organized for better clarity. Descriptive statistics for the five dimensions are presented in Figure 4.2 and 4.3, offering a clear comparison and analysis of the results between the two

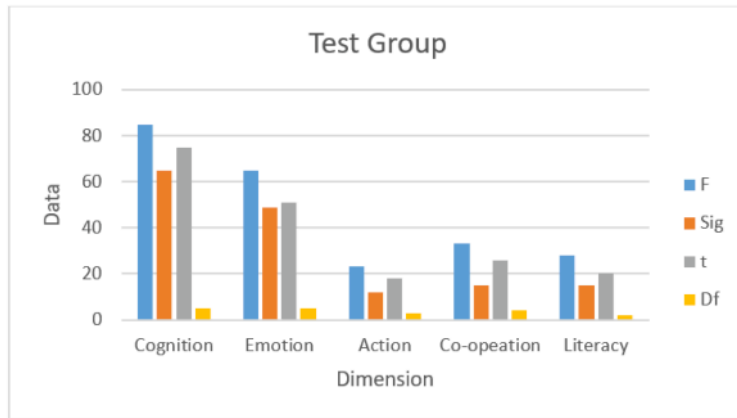


Fig. 4.2: Descriptive statistics for the five dimensions (Test Group)

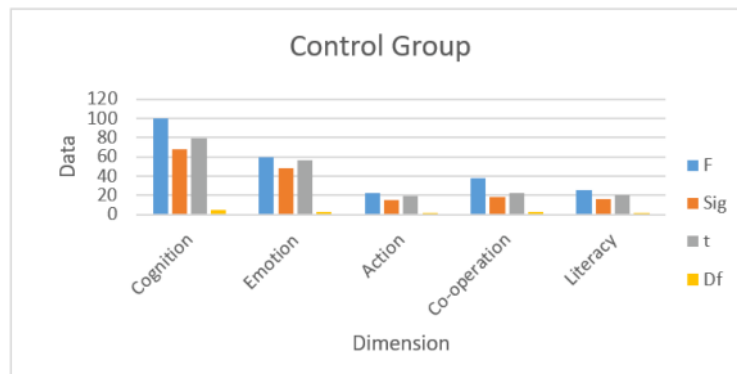


Fig. 4.3: Descriptive statistics for the five dimensions (Control Group)

groups. The F-value (F) , significance (Sig), Test score (t), differences (Df) are used in the analysis features.

The descriptive statistics of questionnaire completed by the students after the experiment were analyzed using OAELT, which incorporates techniques such as Fuzzy AHP and collaborative cloud-fog-edge networking. As depicted in the figure 4.2 and 4.3, the average values of the five dimensions of the students in the experimental group and the students in the control group were found to be similar. This suggests that there is no significant difference in the levels of cognitive, emotional, motor skills, interaction and cooperation, and information literacy between the two groups. To further validate this finding, an independent sample t-test was conducted using SPSS software on the questionnaire data of the experimental group and the control group. The use of OAELT, which incorporates advanced statistical analysis techniques and collaborative learning tools, provided a more accurate and reliable assessment between the two groups. The results of the t-test would help to confirm whether the differences observed in the descriptive statistics of the two groups were statistically significant, further validating the effectiveness of OAELT in facilitating flexible and personalized English learning which is shown in the Table 4.1.

Table 4.1 describing the result of a sample t-test that was conducted to compare two groups of students in terms of several different factors: cognition, emotion, motor skills, cooperation, and literacy. The phrase "no significant difference" means that the differences between the two groups in each of these factors were not statistically significant. In other words, the results of the t-test did not show that the differences between the

Table 4.1: Independent sample t-test before experiment

		F	Sig	t	Df
Cognition	Assuming Equal Variance	4.06	0.03	0.096	117
	Assuming Unequal Variance			0.096	104.78
Emotion	Assuming Equal Variance	1.78	0.28	0.21	117
	Assuming Unequal Variance			0.21	116.08
Action	Assuming Equal Variance	0.50	0.49	0.30	117
	Assuming Unequal Variance			0.30	116.67
Co-operative	Assuming Equal Variance	0.081	0.78	0.64	117
	Assuming Unequal Variance			0.64	116.95
Literacy	Assuming Equal Variance	1.23	0.28	0.25	117
	Assuming Unequal Variance			0.25	115.41

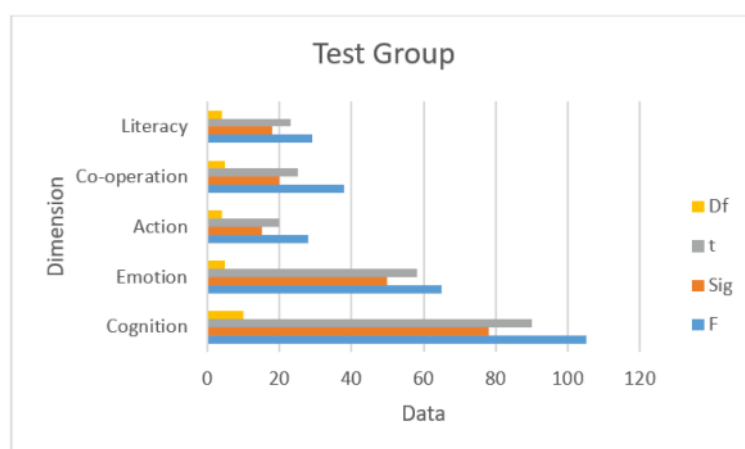


Fig. 4.4: Descriptive statistics of the five dimensions questionnaire for students after the experiment (Test group)

means of the two groups were large enough to rule out the possibility that they were due to random chance. This finding is supported by the data presented in Table 4.1, which presumably shows the means and standard deviations of each group for each of the factors being compared. If the means of the two groups are very similar and the standard deviations are relatively small, this would suggest that there is not a significant difference between the two groups in terms of these factors. The t-test result evaluated using

$$t(df) = t - \text{static}, p = \text{significant value}$$

Using the OAELT, we can conduct experiments to compare and analyze the learning processes and effects of two groups of students. Before the experiment begins, we can conduct an initial assessment or pre-test, which would help us to identify the areas of cognition, emotion, motor skills, interaction and cooperation, and information literacy where the two groups are comparable.

After the experiment, we can use various methods, including experimental observation, written tests, and questionnaire surveys, to analyze the learning processes and effects of the two groups. This surveys would assess the students' cognition, emotion, interaction and cooperation, cooperative learning ability, and information technology literacy. We can use the Fuzzy AHP technique to analyze the data collected from the survey and identify any significant differences between the two groups based on the five dimensions measured by the questionnaire. To analyze the thinking structure of the students, we can use the written test, and the

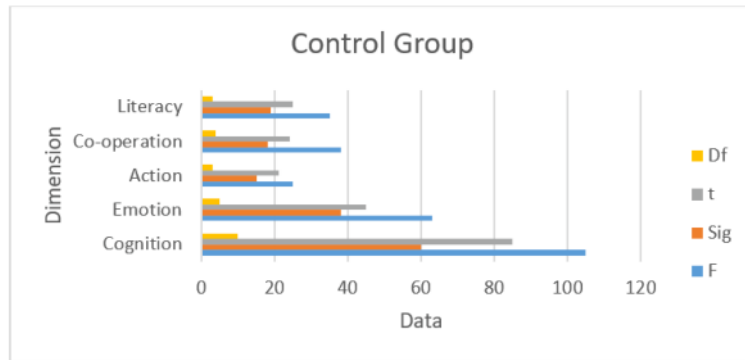


Fig. 4.5: Descriptive statistics of the five dimensions questionnaire for students after the experiment (Control group)

Table 4.2: Independent sample t-test after experiment

		F	Sig	t	Df
Cognition	Assuming Equal Variance	0.67	0.29	6.24	117
	Assuming Unequal Variance			6.24	113.85
Emotion	Assuming Equal Variance	3.74	0.05	5.41	117
	Assuming Unequal Variance			5.41	109.59
Action	Assuming Equal Variance	0.12	0.55	1.82	117
	Assuming Unequal Variance			1.82	116.23
Co-operative	Assuming Equal Variance	0.42	0.38	4.89	117
	Assuming Unequal Variance			4.89	114.71
Literacy	Assuming Equal Variance	4.37	0.02	4.11	117
	Assuming Unequal Variance			4.11	111.85

SOLO layered method can be employed for this purpose. Finally, we can use the collaborative cloud-fog-edge networking technique to create a flexible learning platform that can be accessed from anywhere, at any time, and from any device. With this platform, students can learn English at their own pace and in a way that suits their individual learning styles which is shown in Fig 4.4 and 4.5.

Table 4.2 describing the findings of a study where two groups of students were compared - a "pilot group" and a "control group". According to "Table 4.2", which presumably presents statistical data on the two groups, the pilot group was found to be "substantially significantly dissimilar" to the control group in four dimensions: cognitive, emotional, interaction and cooperation, and information literacy. This means that the two groups were quite different from each other in these areas. More specifically, the students in the pilot group were found to have better cognitive and emotional abilities than those in the control group. They were also found to be better at interacting and cooperating with others during learning activities. However, there was no significant difference between the two groups in terms of motor skills $P > 0.05$, which means that both groups performed similarly in this area. To sum up, the students in the pilot group appeared to be stronger in several key areas related to learning than the control group.

4.2. Experiment of Flexible English learning using OAELT. In this study, a comparative experiment method was conducted to evaluate the effectiveness of autonomous learning for students in the experimental and control groups. The study utilized a combination of questionnaires, interviews, and subjective test papers to gather data on learners' needs, abilities, and comprehension in English language learning. Advanced techniques such as Fuzzy AHP and collaborative cloud-fog-edge networking were used to analyze the results of

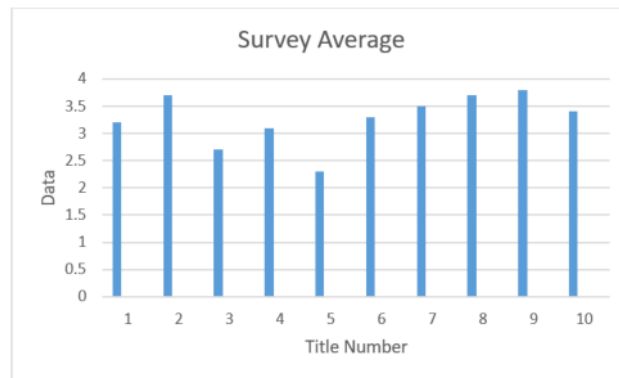


Fig. 4.6: Survey results of student's motivation and interest

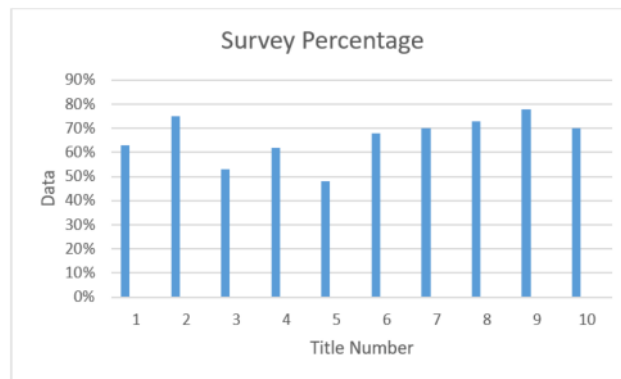


Fig. 4.7: Survey results of student's motivation and interest

the survey and test. OAELT, a flexible English learning platform, was used to support the study and provide personalized learning experiences for the participants. The study's findings, including students' motivation and interest in English language learning, are presented in Figure 4.6 and 4.7. The study's outcomes highlight the importance of personalized support for learners and demonstrate the effectiveness of flexible and personalized learning platforms like OAELT in optimizing learning outcomes.

Based on the OAELT approach, using fuzzy AHP and collaborative cloud-fog-edge for flexible English learning, the data presented in Figure 4.6 and 4.7 suggests that many students may not be fully engaged in autonomous and flexible English learning. The majority of students (63.6%) indicate that they learn English primarily to pass exams, rather than to build their language proficiency and skills. This could be due to external pressure or lack of intrinsic motivation. Additionally, over half of students (53.6%) report that they will not memorize English vocabulary unless assigned recitation homework by their teacher, suggesting a passive and reactive approach to learning. This indicates that they are relying on external cues rather than taking initiative to learn independently. Furthermore, only a minority of learners (45.8%) express confidence in their ability to learn English effectively, indicating that many may lack the self-efficacy and motivation to engage in independent and proactive learning.

Despite these challenges, a significant proportion of students (65.6%) feel that they have gained a lot in learning, indicating that they value learning and its outcomes. The majority of learners (70.8%) also attach importance to learning as a key component of English language acquisition. However, it is important to note that almost three-quarters of students (74.4%) felt the need for training on flexible English learning strategies,

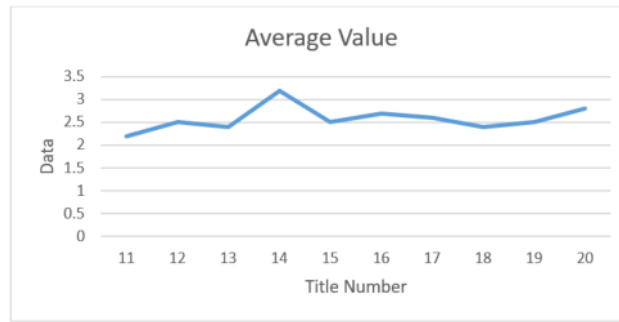


Fig. 4.8: Survey results of students Flexible English learning plans and goals

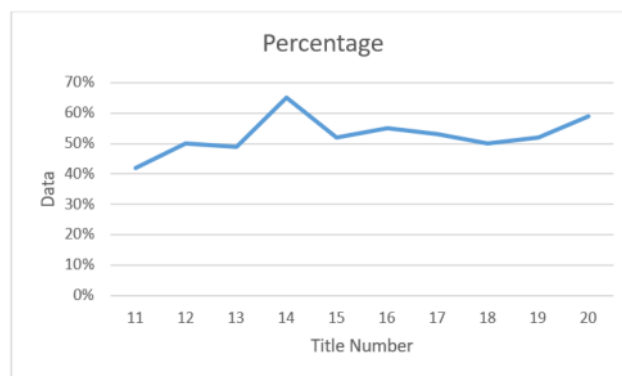


Fig. 4.9: Survey results of students Flexible English learning plans and goals

highlighting the potential benefits of providing students with structured and evidence-based learning resources to support their autonomous learning. By using fuzzy AHP to prioritize these strategies and collaborative cloud-fog-edge to deliver them flexibly, students can access personalized and effective learning materials and support, enabling them to take a more proactive and autonomous approach to their English learning.

Figure 4.8 and 4.9 illustrates the percentage of students who engaged in specific English learning activities. The graph shows that a mere 50.2% of students set goals for learning acquisition, including long-term, mid-term, and short-term objectives. Additionally, 42.8% of students did not establish a personalized learning plan, and 49.2% of students did not allocate a structured study period or prepare a study timetable. Furthermore, only 52% of students developed a periodic review plan for learning, while a significant 59.1% of students reviewed only before the examination.

Here are some potential limitations of the proposed solution and suggestions for future research:

1. **Technology limitations:** While OAELT utilizes cloud-fog-edge networking to overcome some of the limitations of traditional online language learning platforms, there may be technological limitations to its implementation. For example, users may require a high-speed internet connection or advanced hardware to access the platform. Future research could investigate how to mitigate these limitations, such as by developing lightweight applications that can be used on a wider range of devices or providing support to users who may not have access to the necessary technology.
2. **User engagement:** Even with advanced technology, users may not be fully engaged with the platform or motivated to use it. Future research could explore how to improve user engagement with OAELT, such as by incorporating gamification elements, personalization, or social learning features.
3. **Generalizability:** The effectiveness of OAELT may vary across different languages, language proficiency

levels, and learner populations. Future research could investigate how well the platform works across different contexts, as well as identify any potential barriers to implementation or usage.

4. Evaluation metrics: The effectiveness of OAELT may be difficult to measure using traditional evaluation metrics such as language proficiency tests. Future research could explore new evaluation metrics that better capture the unique aspects of the OAELT platform, such as collaboration, information sharing, and technology literacy.
5. Pedagogical approach: While OAELT incorporates collaborative learning and individualized learning approaches, it may not be suitable for all language learning pedagogies or teaching styles. Future research could investigate how OAELT can be adapted to different pedagogical approaches or identify ways to integrate the platform with traditional classroom-based language learning.

5. Conclusion. The conclusion of the paper summarizes, that the main points discussed about the challenges of developing effective online learning tools for English language learners due to the shortcomings of existing systems. These shortcomings include a lack of proper instructional design, limited infrastructure for data sharing, and a lack of connection to motivational theories. To address these issues, this paper proposes a new approach called OAELT, an Online Assisted Learning Tool. OAELT uses a combination of Fuzzy Analytical Hierarchy Process (FAHP) and collaborative cloud-fog-edge networking to create a flexible learning design that adapts to the needs and preferences of individual learners. The FAHP approach tailors the learning design to each learner's unique needs, while the cloud-fog-edge networking approach uses the strengths of each computing layer to deliver a personalized and seamless learning experience. This article also highlights that OAELT employs adaptive and dynamic approaches within a flexible instructional paradigm to ensure effective instructional design. This paradigm facilitates collective learning data exchange across cloud, fog, and edge computing layers. The paper evaluates OAELT's effectiveness using descriptive statistics, which include cognition, emotion, action, co-operation, and literacy. The results demonstrate that OAELT can enhance learning effectiveness and motivation while providing a flexible and seamless learning experience. The findings also suggest that OAELT can provide learners with new learning strategies and curricular readings to improve their flexibility in English learning. Overall, the paper concludes that OAELT's innovative approach has promising potential for enhancing online English language learning, providing a more effective and personalized learning system that overcomes the challenges of modern learning.

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