Hindawi
Mobile Information Systems
Volume 2022, Article ID 4554190, 13 pages
https://doi.org/10.1155/2022/4554190

Research Article

Adaptive Learning Model of English Vocabulary Based on Blockchain and Deep Learning

Jie Li

School of Western Languages, Harbin Normal University, Harbin 150025, Heilongjiang, China

Correspondence should be addressed to Jie Li; lijie@hrbnu.edu.cn

Received 29 April 2022; Revised 17 June 2022; Accepted 27 June 2022; Published 22 July 2022

Academic Editor: Chia-Huei Wu

As one of the three basic elements of language, vocabulary is particularly important when learning English. Nowadays, many students are faced with problems such as boring vocabulary teaching, forgetting quickly after reciting, inefficient vocabulary learning, and lack of initiative. Therefore, it is imperative to seek a scientific and effective teaching mode to improve students' vocabulary achievement. It builds an adaptive learning model of English vocabulary based on blockchain and deep learning, and tests the model. According to the experimental data, 46.8% of the learners will often read English newspapers or magazines to expand their English vocabulary. 50.4% of the students classified and memorized English vocabulary according to different categories. 59% of students often use context to memorize English vocabulary. The results show that before using the English vocabulary adaptive learning model based on blockchain and moderate learning, the average score of students' methods and strategies is in the middle and lower levels. After using the adaptive learning model, some students have been able to use some learning strategies, and a small number of students have expanded their vocabulary through extracurricular reading.

1. Introduction

In June 2001, the Ministry of Education announced a pilot curriculum reform plan. This will be a prelude to a wider curriculum reform. Among the goals of the reform of a school are "to transform the overly important focus of the programme on the delivery of sound content and to highlight the building of attitudes of positive and dynamic study, so as to make the acquiring of elementary skills and a dynamic journey of study and develop appropriate values". "By moving away from an over-focus on memory inertia, rote memorization, and mechanical practice, students are encouraged to actively participate, explore, take serious action, and develop skills in gathering and processing information, acquiring new knowledge, analyzing and problem-solving, communicating, and cooperating". At the same time, education reform requires teachers to pay attention to the the way students learn. The focus should be on developing students' autonomy and independence, respecting their individuality, taking into account the individual differences, and focusing on individualized learning so that each student can reach their full potential. It can be seen that the educational reform requires teachers to respect the individual differences of students and promote personalized learning.

An adaptive learning system is a learning system designed and developed using artificial intelligence techniques based on the learner's model [1]. It is a learning environment that meets the individual needs of learners, both in terms of theoretical study and technical functions. Unlike previous e-learning systems, it focuses on the learners' personal development. This is undoubtedly a trend in digital learning research and development. It is said to be intelligent and advanced mainly because the system can provide learners with a personalized learning mode and dynamically present learning content and resources. It can also use adaptive navigation technology to perform learning diagnosis and learning strategies according to the characteristics of learners [2].

The English vocabulary adaptive learning model based on blockchain and deep learning theoretically improves and enriches the analysis of learner characteristics, constructs the learning style model of the adaptive learning system, and provides a theoretical basis for the design and adaptable study program development. In fact, on the basis of analyzing the existing learning style model, it starts with the new English curriculum standard, summarizes the requirements of the learner's knowledge, ability and literacy in the new curriculum standard, and then analyzes the learner's learning style. In this way, the shortcomings of the traditional single-angle learning style model are overcome, and a learning style model in a comprehensive multi-dimensional adaptive learning system is constructed. In order to improve the intelligence and adaptability of the system, better adapt to the learning process of students, and improve the learning effect of students in the adaptive learning system, the system has added functions for diagnosing students and providing personalized learning strategies, learning tools, and dynamic presentation of the learning content.

2. Related Work

This paper studies some techniques of English vocabulary adaptive learning model, which can be fully applied to the research in this field. Wang X put to discuss the computer corpora for vocabulary training in colleges. Using concepts of estimation, future prospects of employment and rational theory, this text examines the course of a digital computer database in support of the study of college English lexical teaching [3]. In order to assist learners in locating the more interesting language courses, especially vocabulary courses, in an English as a Foreign Language (EFL) environment, Ghaemi investigated the impact of short message services (SMS) provided through social networks on the vocabulary learning process of the EFL learners [4]. Tlili et al. applied learning analysis (LA) method to design an intelligent collaborative educational game to promote English vocabulary learning in primary school students [5]. They provide a number of informative insights that are not recognized by public authorities given the brief time period involved and the fact that the sample samples are quite.

Based on blockchain and deep learning, the following related materials have been read to optimize the adaptive learning of English vocabulary. Iansiti M believed that blockchain is a secure, everlasting, and highly productive transactions with open, balanced, and shared bookkeeping. It can drastically reduce the transaction costs and eliminate intermediaries such as lawyers and bankers [6]. The purpose of Sikorski et al. was to explore the application of the blockchain culture in the fourth coming social change (Industry 4.0) and to show an illustrative case. Among them, it is used to promote a machine to mine (M2M) dynamic and to build an M2M market for power in the background of the petrochemical sector [7]. Kshetri presents the main infrastructure associated with secure network of things on cloud computing relationships. From a security perspective, it was emphasized that blockchain-based solutions can outperform the existing IoT infrastructure largely reliant on focused digital web-based servers in many ways [8]. Olnes et al. believed that as the term indicates, it refers to a set of universal processes for swapping data and digital objects in a global system. The central question he discusses is blockchain enabling government innovations and processes innovation [9]. Pop et al. studied the use of decentralized blockchain mechanisms. It provides transparent, safe, to deliver energy mobility in a timely and secure fashion for all involved flexibility stages market (mainly distribution system operators, retailers, aggregators, etc.) in the form of an energy demand profile adapted to distributed energy consumers [10]. Sharma et al. believed that blogging chain could be used to establish secure, centralized, and intelligent systems for mobility. It can make greater use of the underlying transport system network and support available, and is useful for outsourcing in general techniques [11]. Sharma et al. research proposed a secure social security SDN structure for the Internet of Things (DistBlockNet) built around blockchain enabling security. It is guided by the same tenets as required to engineer a network that is safe, extensible, and energy-efficient architectures [12]. Miraz and Ali believed that Blockchain (BC) is the technology behind the Bitcoin cryptocurrency system. It is attractive and critical to securing increased quality and safety for various applications in many other fields such as the IoT ecosystem [13].

3. Method of English Vocabulary Adaptive Learning Based on Blockchain and Deep Learning

With the development of society and the improvement of China's status in the international arena, language learning, especially English learning, is essential. Improving English vocabulary through adaptive learning using blockchain and deep learning is the first step towards good English teaching.

3.1. Blockchain and Deep Learning. Blockchain is a new technology system that combines multiple technologies. The earliest definition comes from a Bitcoin paper published in 2009. A blockchain is a distributed system where each node is shared by a master machine [14, 15]. Each distributed node encapsulates code and transaction data on the blockchain using a special hashing algorithm and Merkle tree data structure [16]. Blockchain has the characteristics of decentralization and trust. It can establish trust transfer between peers without relying on a third-party trusted authority. This helps reduce transaction costs and improve interaction efficiency.

Homomorphic encryption was proposed in 1978. Homomorphic encryption is a cryptographic technique based on the computational complexity theory of mathematical problems. It processes the homomorphically encrypted data to get an output and decrypts the output. The result is the same output as the unencrypted raw data processed in the same way. Isomorphic ciphering enables algebraic manipulation by consumers on the ciphertext to obtain the result. The same operation is then performed on the same ciphertext result in plaintext. The security parameter λ generated by the male bond p_k is used to decrypt the ciphertext and the public key *sk* is for encrypting the ciphertext. It assumes a plaintext $x \in Z_y$, where y is a large positive integer and Z_y is the set of integers modulo y. It represents the encryption of x as $E_{pk}(x)$. Homomorphic encryption has the following properties:

$$\begin{aligned} E_{pk}(x_1 + x_2) &= E_{pk}(x_1) \oplus E_{pk}(x_2), \\ E_{pk}(a \cdot x_1) &= a \otimes E_{pk}(x_1). \end{aligned} \tag{1}$$

Among them, x_1, x_2 represents the plaintext to be encrypted, and a represents a constant.

The Paillier cryptosystem is an encryption system based on the higher-order residual class problem proposed in 1999. The system has good homogeneous characteristics as well as good homomorphism, can be used to construct a number of useful and highly productive crypto arithmetic systems. Threshold variants of the Paillier cryptosystem not only possess additive homomorphism, but also satisfy the design of threshold cryptosystems [17].

A version of the pyramidal password scheme with (p, t)-threshold is adopted, whereby the double key sk is divided and distributed to party p. Instead, every side is given an integral double pass key. If a side wishes to exactly decrypt crypto copy c, it has to cooperate at least $t - 1$ with the other party. In the demystification operation, every side i $(1 \le i \le p)$ takes use sk_i to calculate the partial decryption.

$$c_i = c^{x \Delta sk_i}. \tag{2}$$

Among them, $\triangle = p$! Based on the combination algorithm, in order to obtain the plaintext x, at least the decryption result of the t party needs to be combined.

Letting Γ_1 and Γ_2 be two multiplicative cyclic groups of order prime p. g_1 and g_2 are generators of Γ_1 and Γ_2, respectively, and Ψ is the isomorphic map of Γ_1 to Γ_2, where $\Psi(g_2) = g_1$. A bilinear pair can be defined as:

$$\Gamma = (y, \Gamma_1, \Gamma_2, \Gamma_T, e, g_1, g_2) G_1 = \langle g_1 \rangle, G_2 = \langle g_2 \rangle, \tag{3}$$

A is a multiplicative group of order y. Bilinear mapping:

$$e: \Gamma_1 \times \Gamma_2 \longrightarrow \Gamma_T. \tag{4}$$

If e has the following properties:

Bilinear:

$$\begin{aligned} &\forall u \in G_1, v \in G_2, \\ &a, b \in Z_y: e\left(u^a, v^b\right) = e(u, v)^{ab}. \end{aligned} \tag{5}$$

Non-degenerate, exists:

$$\begin{aligned} &u \in \Gamma_1, v \in \Gamma_2, \\ &e(u, v) \ne O. \end{aligned} \tag{6}$$

Among them, O is the identity element of Γ_T.

Computability: It exists efficient polynomial time algorithm to compute $e(u, v)$. For any $u \in \Gamma_1$, $v \in \Gamma_2$.

Bilinear mapping plays a key role in the collaborative sharing of big data. In particular, the bilinear mapping structure is used to construct a data cooperative sharing scheme. The combination of bilinear mapping with multi-party secure computing and other technologies that play an important role in the collaborative sharing of big data is of great significance [18].

The idea of deep learning is actually derived from the working mode of the human brain. Understanding how the human brain works can lead to a better understanding of the deep learning. In fact, when the human brain processes external information, it is a process of iterative abstraction and conceptualization of signals.

The following three parts are the basic structure of a convolutional neural network: the first part is the input layer, which represents the input image. The second part consists of several convolutional layers, combining nonlinear activation and aggregation operations to complete image feature extraction. The third part consists of a fully concatenated layer, similar to a multi-layer perceptron that completes the classification of features [19].

The first neuron of the output layer is connected to the first 3×3 part of the input data. The second neuron connects to the second part, and so on. The output formula for each neuron is as follows:

$$f(x) = \operatorname{act}\left(\sum_{i,j}^{b} \theta_{(b-i)(b-j)} x_{ij} + c\right). \tag{7}$$

For two-dimensional discrete functions $f(x, y)$ and $g(x, y)$, their convolutions are defined as follows:

$$f(a,b)^* g(a,b) = \sum_{u}^{\infty} \sum_{v}^{\infty} f(u,v) g(a-u, b-v). \tag{8}$$

A convolutional operation in a convolutional layer is usually followed by an activation layer. Simply put, the task of an activation function in a neural network is to transform a linear input into a nonlinear input. A neural network without an added activation function can be considered a linear model with a certain degree of unpredictability. Many problems are linearly indivisible, so it is necessary to introduce nonlinear factors to improve the nonlinear expression ability. At present, there are several sigmod and Tanh methods and ReLu methods are frequently applied. The activation function in the convolutional layer is widely used ReLu function. The function formula of ReLu is as follows:

$$f(x) = \begin{cases} x, & x \ge 0, \\ 0, & x < 0. \end{cases} \tag{9}$$

The benefit of using the ReLu activation function is that it simplifies the computation of the backpropagation algorithm. The convergence speed in gradient descent is accelerated without the problem of vanishing gradients [20].

In the structure of convolutional neural networks, pooling layers are added periodically between successive convolutional layers. The main function of the pooling layer is to gradually reduce the two-dimensional size of the feature map. It effectively reduces the number of network parameters and the amount of calculation, and also reduces the risk of network training overfitting. Pooling is actually a merge operation. The value of a region is replaced by a value, which can be the average, maximum, minimum, etc., of the region. The pooling operation summarizes the features of the input feature map, separates the main features, and simplifies the computational complexity of the network.

There is a special computational processing layer in some convolutional neural network models, which is called the local response normalization (LRN) layer. It is usually after activation functions and redundant operations. The processing performed by the LRN is to smooth the output of the current layer. The number of corresponding positions of the preceding and following layers smoothes the constraints of the middle layer. The calculation formula is as follows:

$$b_{m,n}^{i} = \frac{a_{m,n}^{i}}{\left(k + \alpha \sum_{n=\max(0,i-y/2)}^{\min(Y-1,i+Y/2)} \left(a_{m,n}^{j}\right)^{2}\right)^{\beta}}. \tag{10}$$

Fully connected layers (FC) are usually the last few layers in the whole network. In the fully linking levels, each neuron is linked to every other neuron in the layer prior to it, so the number of parameters in the fully connected layer is the largest. The fully connected layer acts as a “classifier” in the network. Its previous convolutional layers have already extracted features from the image. It needs to synthesize these features into a one-dimensional feature vector, and send its output value to a classifier (such as a softmax classifier) to obtain the classification result [21].

3.1.1. Blockchain. As known as being one of the latest technologies to revolutionise the market in the last few months, the blockchain’s typical and successful use is the renowned bitcoin, a new digital coin. But after nearly 9 years of development, blockchain has long existed independently of Bitcoin. Its outstanding features such as decentralized trust and complete distribution have subverted traditional industries such as finance, medical care, and the Internet of Things to a certain extent. The application prospect is very broad. From a literal point of view and a data structure point of view, a blockchain can be divided into two data structures: block and chain [22]. A block refers to a digital block that stores all the transactions over a period of time. A chain refers to a continuous and sequential unique chain structure consisting of interconnected blocks with timestamps. Technically, a blockchain can be thought of as a distributed public database (or public ledger). It consists of several key elements. The blockchain technology mainly includes five key elements: modern cryptography, distributed point-to-point network communication technology, decentralized consistency consensus algorithm, incentive mechanism, and programmable script code. From the perspective of participating parties, it can be divided into private blockchain, public blockchain, and alliance blockchain. The public chain is open to the whole network. All users can access all the information of blockchain nodes and participate in transaction activities without authorization, which can be completely decentralized in a practical sense. At present, there are the more typical public chains such as Bitcoin and Ethereum. It is jointly maintained by the entire network, so it is extremely secure and is often used in scenarios such as digital currency, electronic finance, and e-commerce. The alliance chain is composed of member nodes participating in the alliance. Unlike the public chain, the consensus rules of the blockchain network are jointly agreed by the member institutions.

In general, the blockchain architecture includes from bottom to top: data layer, network layer, and consensus layer. The motivation, contract, and utility tiers are not needed for just every single zone chain application. The basic framework of blockchain is shown in Figure 1:

The application scenarios of the application layer and blockchain include digital currency, data authentication, financial transactions, and other fields, as well as some nontraditional applications. The contract layer encapsulates various scripts and smart contracts, enabling the blockchain system to achieve programmable features and adapt to various business logics in the society. Bitcoin uses a simple, stack-based scripting language that is not Turing complete. Ethereum developed a complete Turing scripting language to create smart contracts for more complex and precise applications. The incentive layer integrates financial elements into district chains, including a mechanism for issuing and distributing economic incentives. The consensus layer contains various consensus algorithms or consensus protocols between nodes in the blockchain system. It is the key to ensuring the accuracy and consistency of incoming data, and is the core technology of blockchain. The network layer includes P2P network mechanism, data distribution, and control mechanism. The data layer encapsulates the underlying block structure and chain structure. It includes technologies such as asymmetric encryption, digital signatures, timestamps, Merkle Tree, and hash functions. It is these technologies that build the tamper-proof, traceable foundation of blockchain. The following three layers are necessary elements to build a blockchain. No blockchain can be called a true blockchain without one of these layers.

Blockchain is a decentralized data storage architecture that combines cryptography, distributed technology, economic games, and contracts. Among them, cryptography provides security for data storage and transmission. Distributed consensus algorithms are used to validate data or validate updates to the validated data. The contract part mainly refers to smart contracts, which realize trustless transactions through automatic code execution. In a narrow sense, a blockchain is a distributed hyperledger with decentralized properties, where information is tamper-proof and traceable. A blockchain is just a data structure in which all the valuable information can be stored. It can be extended and shared among different clients due to peer-to-peer (P2P) architecture. However, because of the encryption used, it is impossible to change some data without the proper private key. What’s more, all changes are stored on-chain and are made public forever. It consists of interconnected blocks (linked lists). Each block contains a series of transactions made at a certain point in time (timestamp).

Modern cryptographic methods form the basis of blockchain security. These algorithms first include hash algorithms, merkle tree verification, and elliptic curve encryption algorithms. A function that can compress any length of information into a fixed-length binary string in a given amount of time is called a cryptographic hash

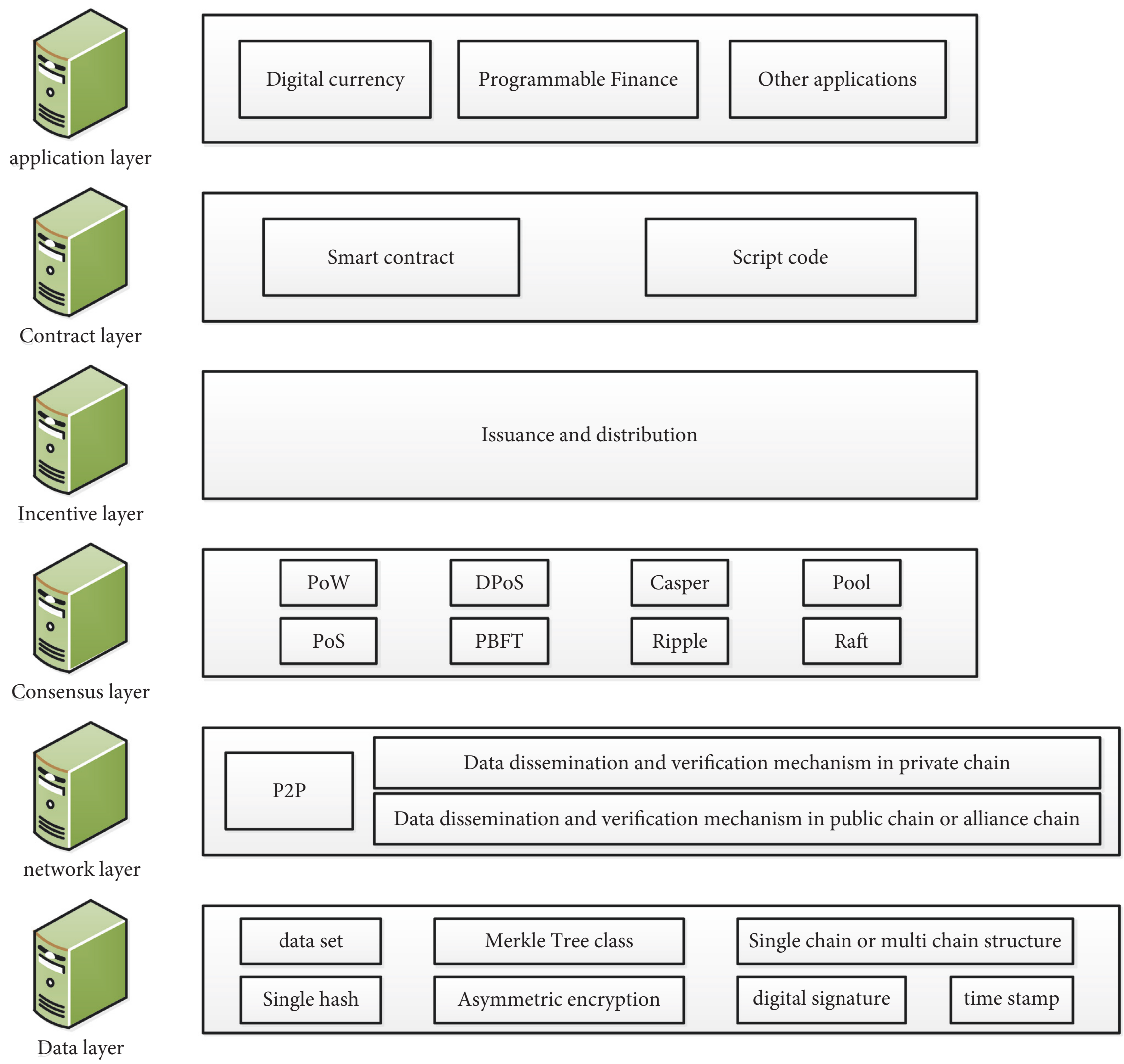

Figure 1: Blockchain basic framework.

function. The output value of this function is called the hash or hash value. Cryptographic hash functions are commonly used in the generation of public and private keys, block construction, and consensus establishment in blockchains. The three main characteristics of the cryptographic hash function can theoretically effectively guarantee the security of the blockchain:

(1) Anti-collision: if two different information processed by the same cryptographic function output the same hash value, it is called collision. Therefore, the algorithm can ensure the integrity of the block and the information will not be maliciously tampered with during the interaction process;

(2) Irreversibility: means that the original information cannot be restored through the hash value;

(3) Puzzle-Friendly: a hash function is called puzzle-friendly, where the input value is random and it is difficult to find another value. The resulting hash is exactly y. So, if someone wants to lock a hash function to produce a special output y, the computational difficulty is the same, which is the basis of PoW;

(4) Hash pointer chain: the hash pointer includes a pointer to the address of the previous block and a hash value generated by encryption of this data information. It is used to verify whether the retrieved information has been illegally altered.

A Merkle hash tree is a binary or multi-dimensional hash tree. Its leaf nodes contain the cryptographic hash of each transaction block. Its non-leaf nodes contain hash values jointly computed by these leaf nodes. In the computer field, Merkle trees are mostly used for integrity verification processing. In a distributed environment, the amount of data transmission and the computational complexity are reduced. After receiving the data, it is only necessary to verify that the root nodes of the Merkle tree on both sides are consistent. If the data is tampered with, the wrong data location can be quickly located through the tree. The blockchain Merkle tree structure is shown in Figure 2:

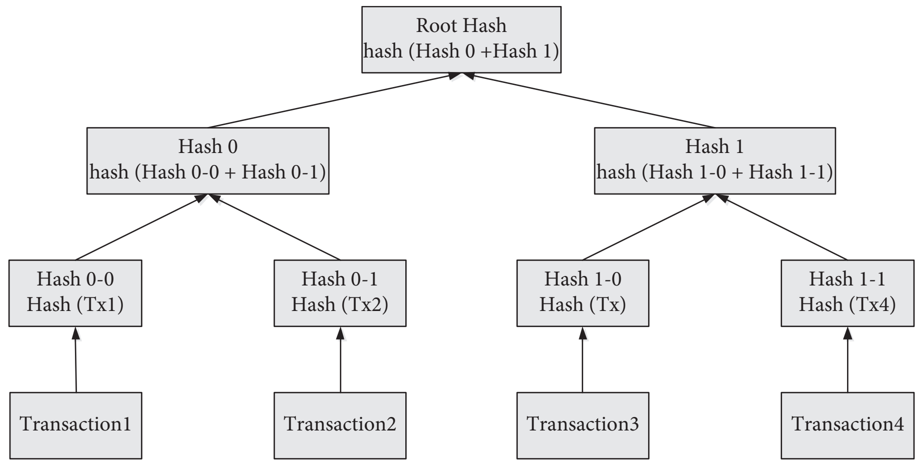

Figure 2: Blockchain Merkle tree structure.

Public key encryption algorithms are also known as asymmetric algorithms. Because different ciphers are used for encryption and decryption, the public key is used to encrypt data, and only the private key can decrypt it, and vice versa. The public key algorithm used by the Bitcoin blockchain is Elliptic Curve Cryptography (ECC). The public key is used as the public address of the transaction and the private key is used for information encryption. This is also called signing the message. Its security is guaranteed by the elliptic curve discrete logarithm problem.

3.1.2. Deep Learning. In the context of globalization and the increasing internationalization of China, the demand for English courses is growing rapidly. However, due to the great difference in pronunciation between Chinese and English, there is a lack of English learning environment and a lack of good English teachers. However, traditional classroom teaching cannot satisfy English learning due to the limitation of time and place. Various reasons have combined to make English teaching and learning become a major problem in China.

Deep Learning (DL) originated in the field of machine learning [23]. It aims to build and simulate the deep neural network (DNN) of the human brain for analysis and learning. DNN shows outstanding advantages in solving some complex problems. The reason is that it can better simulate the multilayer depth transmission of human brain neurons to interpret the data. And deep learning in education and teaching is usually considered by two researchers based on the difference between surface learning and deep learning. On this basis, scholars from various countries have carried out corresponding research. At present, many experts and scholars have different definitions of deep learning. Deep learning is defined as a state or process of learning [24]. It can enhance students' understanding of knowledge, improve their learning initiative, transfer ability, and interlinkage of subject knowledge. It improves the understanding of the nature of knowledge and the mastery of higher-order thinking.

Conditional random field model (CRF) is an undirected graph discriminant model for sequence labeling in the field of machine learning. CRF is mainly used in application scenarios such as word segmentation, text annotation, and named entity recognition in the field of natural language processing (NLP). The structure diagram of the chain CRF is shown in Figure 3:

Based on the concept of words, the CRF model transforms the word separation problem into a classification problem. Sequence prediction is determined by assigning to each word the information that the word contains (the position of each word within the word).

"Deep learning" is a way and method of learning. It focuses on real-life situations and complex technological environments. It promotes deep processing of knowledge and information, deep understanding of complex concepts, and deep learning of meaning. It actively builds a body of personal knowledge and transfers it to the real world to solve complex problems. Ultimately, it supports the achievement of overall learning goals and general educational goals and the development of higher-order thinking skills. Since 1976, "deep learning" and "shallow learning" have been proposed simultaneously as two corresponding concepts. Any subsequent research on deep learning is almost always a comparative analysis study on the basis of shallow learning. Compared with shallow learning, deep learning has good performance in four dimensions: cognitive outcome, target level, thinking ability, and learning behavior. The composition of deep learning capabilities is shown in Figure 4:

Learning assessments are based on the learner's learning objectives. It provides relevant assessments of learning processes and outcomes, facilitating reflection on learning processes and validation of learning objectives. Assessments of learning objectives are usually done through observations, questions, tests, and other methods. At the same time, deep learning has common characteristics with general learning. Therefore, assessing the impact of deep learning should also be done from three perspectives: cognition, motor skills, and emotion. In addition to the characteristics of general learning, the core of deep learning is the characteristics of higher-order thinking. On this basis, one researcher believes that the assessment of deep learning is an interconnected organic whole that spans four dimensions: cognition,

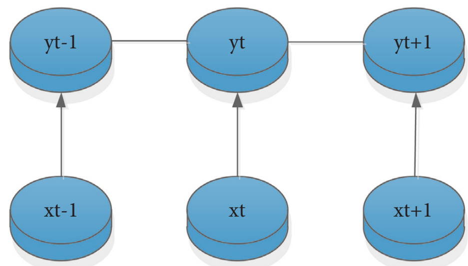

Figure 3: Chain CRF structure diagram.

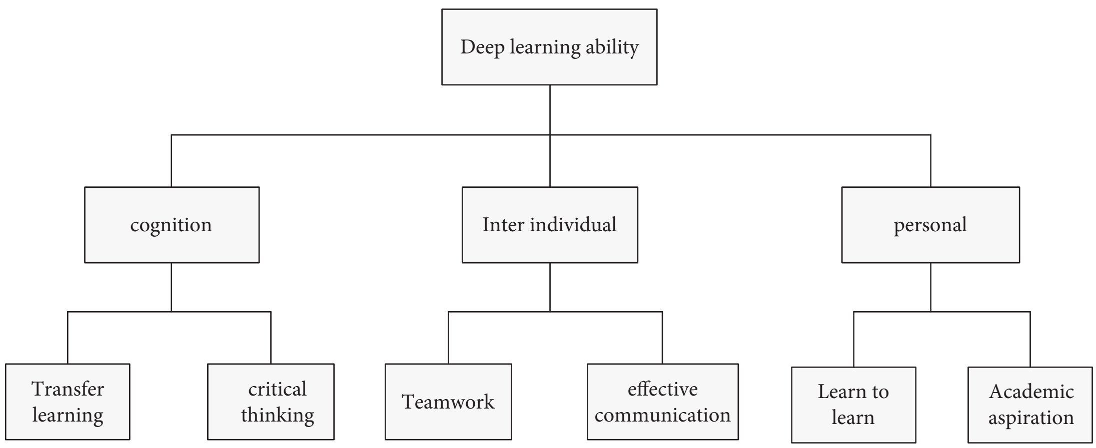

Figure 4: Composition of deep learning capabilities.

movement, emotion, and mental structure. Therefore, a deep learning evaluation system for cognition, movement, emotion, and thinking is proposed, and a detailed level division of the learning effect of each dimension is proposed.

3.2. English Vocabulary Adaptive Testing System. Item response models are mathematical models that explain participants' responses to items in a probabilistic manner. There are many different types of item response models, including Lord's normal oval curve model, Logistic model, and Rasch model. The item response model contains three parameters, namely, difficulty, discrimination, and ratio. According to the number of parameters included in different models, it can be divided into one-parameter, two-parameter, and three-parameter models.

Adaptive response models are mathematical models that rationally explain participants' responses to questions. There are many types of models, including Rasch model, Lord's normal oval curve model, and Logistic model. The model has three parameters, difficulty, insight, and scale. According to the number of parameters of each model, it can be divided into single, double, and three parameter models. The item feature function expressions of each logistic model are as follows:

One-parameter model:

$$P_j(\theta) = \frac{e^{(\theta - b_j)}}{1 + e^{(\theta - b_j)}}. \tag{11}$$

Two-parameter model:

$$Pj(\theta) = \frac{e^{Daj(\theta - bj)}}{1 + e^{Da\ j(\theta - bj)}}. \tag{12}$$

Three parameter model:

$$Pj(\theta) = Cj + (1 - Cj)\frac{e^{Daj(\theta - bj)}}{1 + e^{Daj(\theta - bj)}}. \tag{13}$$

In the formula, $D = 1.702$. j represents the title number. θ represents the subject's ability estimate. a represents the discrimination degree of the jth question. b indicates the difficulty of the question. c is the guessing coefficient of the question.

One-parameter and two-parameter models are relatively simple. The calculation process is not complicated, and the calculation part can be ignored. The accuracy of parameter estimates is therefore only slightly affected by the choice of one- or two-parameter model. The three-parameter model is more suitable for more complex test procedures [25].

The specific process of adaptive testing is divided into two parts: the baseline evaluation stage and the refinement evaluation stage. The most important feature of the adaptive learning system is the ability to continuously evaluate the performance based on the responses of the subjects, and extract new tasks from the question bank that are suitable for the performance of the subjects. Therefore, the method for continuously selecting questions from the question bank is one of the most important issues in developing adaptive learning systems.

The information function of the item depends on the subject's ability level θ. It also indicates how much information the item can provide, denoted as $J_j(\theta)$, namely,

$$J_j(\theta) = \frac{\left[P_j(\theta)\right]^2}{P_j(\theta)Q_j(\theta)} \, (j = 1, \ldots, n). \tag{14}$$

Among them, $J_j(\theta)$ represents the amount of information provided by item j when the subject's ability is θ. $P_j(\theta)$ is the response function of the subject with ability θ on item j. $P_j(\theta)$ represents the first partial derivative of the item response function $P_j(\theta)$ with respect to θ, and

$$Q_j(\theta) = 1 - P_j(\theta). \tag{15}$$

Substituting the one-parameter model formula into:

$$J_j(\theta) = \frac{e^{\left(\theta - b_j\right)}}{\left[1 + e^{\left(\theta - b_j\right)}\right]^2}. \tag{16}$$

It can be deduced from the formula that the amount of information provided by the test item varies with the ability level θ of the test solver. The value of the task information function is related to the value of the task difficulty b and the value of the subject's ability. And it is not affected by one factor, but by two factors. The smaller the difference between the value of task difficulty b and the subject's ability value, the higher the value of the information function and the more accurate the ability estimate [26].

If a quiz consists of multiple items, a new function, the quiz information function, needs to be introduced. The information function of a test is the sum of its test item information functions at a certain value of θ. If the test consists of more than one element, a new function must be introduced—the test information function. The θ value of the test information function is the sum of the test item information functions, denoted as $J(\theta)$. Its mathematical expression is as follows:

$$J(\theta) = \sum_{j=1}^{n} J_j(\theta). \tag{17}$$

The above formula shows that, according to the item independence assumption of item response theory, the amount of information that each test item can provide is not affected by other test items. The value of the quiz information function is equal to the sum of the item information functions of all the questions contained in the quiz.

The test information function is denoted as $SE(\theta)$, namely,

$$SE(\theta) = \frac{1}{\sqrt{J(\theta)}}. \tag{18}$$

It can be seen from the formula that when the value of θ reaches the maximum, the value of the standard error is the smallest, that is, the estimated value of θ is the most accurate at this time.

3.2.1. Adaptive Learning of English Vocabulary. Small vocabulary and insufficient vocabulary use are a common problem for English learners and all learners of English as a second language. In traditional classroom teaching, students' vocabulary learning is mainly limited to the teacher's teaching in the classroom. Students passively absorb the knowledge imparted by teachers, lack of awareness, and self-learning methods. The teacher's teaching is for all students, and the focus of teaching is to learn English vocabulary. The same vocabulary course is adopted for all students without taking into account the vocabulary foundation and memory of different students, resulting in unsatisfactory teaching effect. For example, students with larger vocabulary and better retention feel comfortable in class. However, students with weak vocabulary and poor retention ability cannot absorb the knowledge taught by the teacher well, and achieve poor learning effect in the classroom. In addition, students do not know their vocabulary level and memory ability, and cannot learn vocabulary outside of class. They cannot choose the vocabulary to memorize reasonably, and cannot choose the appropriate vocabulary learning method according to their memory ability. It leads to low vocabulary learning efficiency for some students, especially those with poor autonomous learning ability. Learning gets half the result with twice the effort, learning motivation is reduced, and students have less vocabulary. The English grades are not ideal and even have aversion to the learning and memory of English vocabulary.

Preliminary interviews and surveys show that, due to insufficient vocabulary, most of the students' English comprehension and expression abilities are seriously affected, and vocabulary usage is weak. This is contrary to the English use, listening and speaking ability that students want to achieve, and seriously restricts students' English development. In the current research, it is found that the current students have problems in vocabulary learning methods and vocabulary learning effects. It is mainly reflected in the following three aspects: 1. Most students use mechanical skills in vocabulary learning and lack content skills. 2. It lacks of understanding of the importance of vocabulary learning and the methods of vocabulary learning. 3. It lacks of vocabulary learning plan. Most high school students do not have their own vocabulary learning plans, and cannot properly learn the vocabulary they need to master in stages and in a timely and appropriate amount.

Adaptive learning stands for "adapt, adjust". That is, "adaptability is strong". Learning outcomes are influenced by a variety of differences between learners (including learning styles, backgrounds, personal abilities, learning goals, and thinking patterns). And the changes in the knowledge structure of the same learner during the learning process will also affect the learning results accordingly. This makes the inadequacy of model-based unified teaching more and more obvious. Adaptive learning support systems have emerged, offering a range of individually tailored learning support systems that take into account individual differences in the learning process. Adaptive learning is essentially a personalized learning support system. It provides tailored and personalized learning content and strategies according to the different characteristics of different learners. Adaptive learning is actually learning that focuses on individual differences. It is a highly personalized learning process that adapts the learning environment, learning content, and learning activities to the different characteristics of each individual. It can be said that it is a kind of learning that varies from person to person and is full of personality.

Adaptive learning is similar to personalized learning, but there are differences. There are different approaches and modes of personalized learning, including competency-based learning, differentiated learning, learning models, and adaptive learning. Adaptive learning is a specific method for implementing the personalized learning. It is based on the analysis of learning data to obtain information about learner skills and preferences. Then, provide relevant content to learners on this basis.

Depending on the content and learning style, people's learning can be divided into mechanical, didactic, and adaptive. Adaptive learning is a process. It engages students actively to acquire knowledge and skills in different areas by using practical examples and problem-solving methods, and by experimenting with different ways of acquiring information. Adaptive learning is an active, learner-centered learning process. It allows learners to monitor their own learning process and choose the content and learning style or strategy that best suits them.

4. Experiment of Deep Learning English Vocabulary Adaptive Learning

4.1. Practice of Deep Learning. The experiment takes the SPOC proprietary course on the MOOC platform of Chinese universities as an example for comparison. There are 1 lecturer, 1 postgraduate assistant, and 120 students in the experiment. These students are from two classes of the same grade at Sichuan Normal University. Among them, the experimental group and the control group each had 60 students [27].

In the preparation stage of the experiment, firstly, the research object's attitude to online learning, online learning experience, and willingness to serve as a scholar were investigated through questionnaires. A total of 120 questionnaires were distributed, and 120 valid questionnaires were returned. The favorite teaching mode diagram is shown in Figure 5:

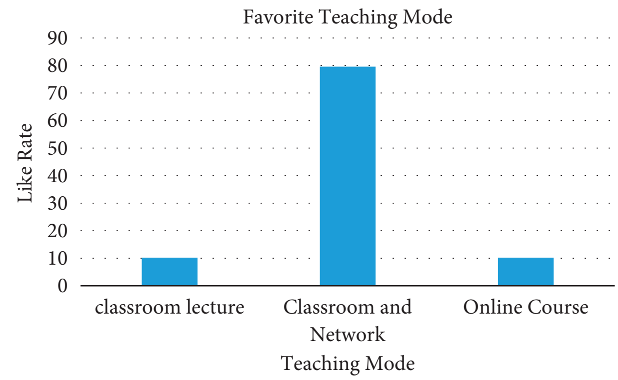

Figure 5: Favorite teaching mode.

It can be found from the figure that 79.61% of the students in the experimental group like the teaching mode that combines course teaching and online learning. Students prefer a combined learning model to a single learning model. This laid the foundation for the development of SPOC courses.

Referring to the goals and evaluation system of deep learning, a deep learning questionnaire was designed before the experiment. It investigated the cognitive state, emotional state, motor skills, interaction and cooperation, and information technology literacy of the students in the experimental and control groups. To make the data clearer, the data has been combed. Descriptive statistics for the five dimensions are shown in Figure 6:

As can be seen from the figure, the average values of the five dimensions of the students in the experimental group and the students in the control group are not much different. SPSS software was used to conduct independent sample t-test on the questionnaire data of the experimental group and the control group. The independent sample t-test table before the experiment is shown in Table 1:

It can be found from Table 1 that there is no significant difference between the two groups of students in terms of cognition, emotion, motor skills, interaction and cooperation, and information literacy.

After the experiment, through experimental observation, written test and questionnaire survey, the learning process and learning effect of the two groups of experiments were compared and analyzed from the perspective of students. Among them, using the deep learning effect questionnaire, the second questionnaire survey was conducted on the cognition, emotion, interaction and cooperation, cooperative learning ability, and information technology literacy of the students in the experimental group and the control group. For the thinking structure, the method of written test was adopted, and the SOLO layered method was used for analysis. The descriptive statistics of the five dimensions of the deep learning questionnaire of the students after the experiment is shown in Figure 7:

It can be seen from Figure 7 that in the cognitive dimension and emotional dimension, the average score of the experimental group is significantly higher than that of the control group. The independent sample t-test table after the experiment is shown in Table 2:

From Table 2, it is found that the students in the pilot group were substantially significantly dissimilar to the control students in four aspects: cognitive dimension, emotional dimension, interaction and cooperation dimension, and information literacy dimension. There was no significant difference in motor skills dimension, $P > 0.05$. To sum up, the students in the experimental group were stronger than the control group in terms of cognitive goals, emotional goals, and motor skills. They have stronger ability to interact and cooperate in learning.

4.2. Experiment of English Vocabulary Learning. In this study, a comparative experiment method was used to conduct experiments on the students in the experimental

Table 1: Independent sample t-test before experiment.

		F	Sig	t	Df
Cognition	Assuming equal variances Assuming unequal variances	4.048	0.045	0.097 0.097	117 104.759
Emotion	Assuming equal variances Assuming unequal variances	1.177	0.279	0.204 0.204	117 116.047
Action	Assuming equal variances Assuming unequal variances	0.491	0.483	0.298 0.298	117 116.656
Cooperate	Assuming equal variances 1 Assuming unequal variances	0.081	0.773	0.634 0.634	117 116.949
Literacy	Assuming equal variances Assuming unequal variances	1.224	0.270	0.240 0.240	117 115.402

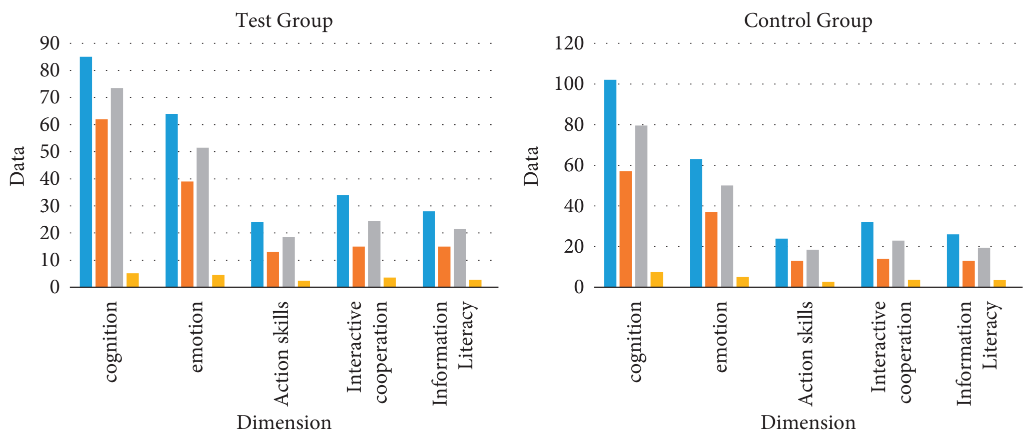

Figure 6: Descriptive statistics of the five dimensions of the deep learning questionnaire for students before the experiment.

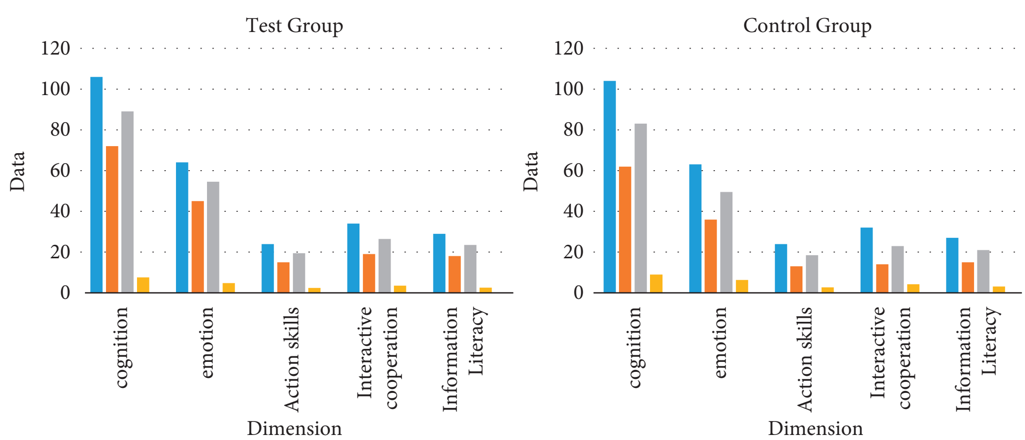

Figure 7: Descriptive statistics of the five dimensions of the deep learning questionnaire for students after the experiment.

group and the control group. Based on the results of analyzing questionnaire data and interviews, it understands the support that the learners need in vocabulary autonomous learning. It distributes test papers to learners in the experimental and control groups. The question types of the test paper are divided into English-Chinese translation of words, English-Chinese translation of phrases, completion of sentences according to Chinese, completion of sentences according to the first letter, writing words according to the context of dialogue, conversion of synonyms, and cloze. The test papers are all subjective questions, which examine the students' abilities in vocabulary use, contextual comprehension, and discourse comprehension to test their vocabulary learning, cognition, and use levels. The results of the survey of students' motivation and interest in autonomous learning of English vocabulary are shown in Figure 8:

Figure 8 shows that 63.6% of students learn English vocabulary because of the need for exams. 53.6% of students will not memorize English vocabulary as long as the teacher

Table 2: Independent sample t-test after experiment.

		F	Sig	T	Df
Cognition	Assuming equal variances Assuming unequal variances	0.663	0.284	6.233 6.233	117 113.841
Emotion	Assuming equal variances Assuming unequal variances	3.730	0.043	5.401 5.401	117 109.586
Action	Assuming equal variances Assuming unequal variances	0.116	0.543	1.810 1.810	117 116.226
Cooperate	Assuming equal variances 1 Assuming unequal variances	0.411	0.376	4.884 4.884	117 114.707
Literacy	Assuming equal variances Assuming unequal variances	4.365	0.027	4.102 4.102	117 111.842

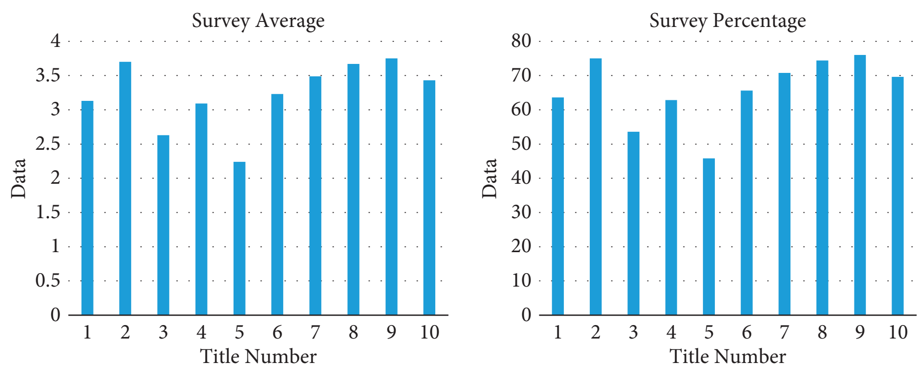

Figure 8: Survey results of students' motivation and interest in autonomous learning of English vocabulary.

does not assign English vocabulary recitation homework. Only 45.8% of learners have confidence in vocabulary learning. 65.6% of the students feel that they have gained a lot in vocabulary learning. 70.8% of the learners feel that vocabulary learning is the key to English learning and therefore attach importance to vocabulary learning. 74.4% of the learners felt the need for training on vocabulary learning strategies.

From the graph data, it can be concluded that most learners have realized that English vocabulary learning is important. They believe that there is a great gain in vocabulary learning and hope to get training in learning strategies. But most of these students learn English vocabulary because of the need for exams and under pressure from teachers. The results of the survey of students' English vocabulary autonomous learning goals and plans are shown in Figure 9:

Figure 9 shows that only about 50% of students set long-term, mid-term, and short-term goals for vocabulary learning. 43.4% of the students did not make their own vocabulary learning plan. 48.6% of the students did not make a vocabulary study timetable and did not systematically arrange the best study time. Only 51.6% of the students made a periodic vocabulary review plan for themselves. 58.4% of the students reviewed vocabulary only before the test. The results of the survey of students' English vocabulary autonomous learning methods and strategies are shown in Table 3:

The data in Table 3 shows that only 46.8% of the learners will often read English newspapers or magazines to expand their English vocabulary. 67.6% of learners rely on teaching materials and teacher's explanation for learning English vocabulary. 50.4% of the students classified and memorized English vocabulary according to different categories. 68.2% of the students kept reading or copying the words when they recited the vocabulary until they could dictate them. 66.8% of the students looked up the dictionary whenever they encountered an unfamiliar word. 59% of students often use context to memorize English vocabulary. The results of the survey on monitoring and evaluation of students' autonomous learning of English vocabulary are shown in Table 4:

The data in Table 4 show that 56.8% of the students cannot learn vocabulary according to the preset plan. 54.8% of the learners can overcome the interference from themselves or the outside world and insist on learning English vocabulary. 56.6% can adjust their learning methods in time in English vocabulary learning. 54.8% of the students did not test their mastery of vocabulary after learning. 55.4% of the students did not summarize the reasons for their mistakes after vocabulary learning. 54% of students do not evaluate their learning methods and improve them after vocabulary learning. Only 48.2% of the students will make a summary and generalization of their vocabulary learning in one month. It can be concluded from the data in the table. Nearly half of the students have been able to manage their vocabulary study time as planned. They can also overcome their own or external interference and continue to learn in the original planned vocabulary learning.

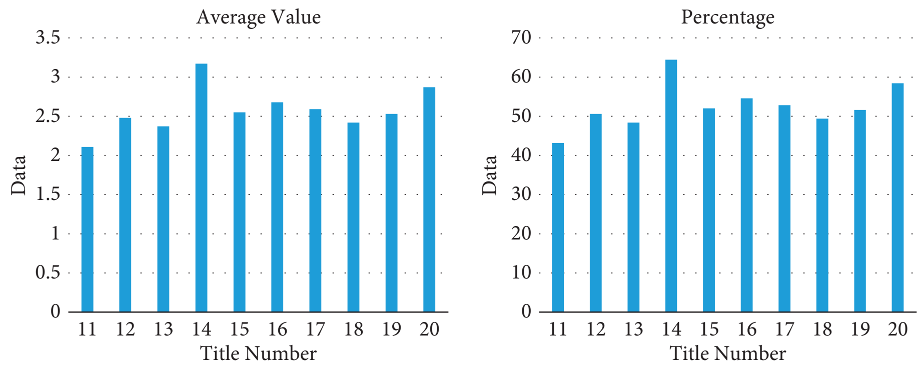

Figure 9: Survey results of students' English vocabulary autonomous learning goals and plans.

Table 3: Survey results of students' English vocabulary autonomous learning methods and strategies.

Title number	Average value	Percentage (%)
21	2.29	46.8
22	3.10	63
23	3.33	67.6
24	2.47	50.4
25	3.36	68.2
26	2.85	58
27	2.56	52.2
28	2.78	56.6
29	3.29	66.8
30	2.90	59

Table 4: Survey results of monitoring and evaluation of students' autonomous learning of English vocabulary.

Title number	Average value	Percentage (%)
31	3.04	61.8
32	2.79	56.8
33	2.62	53.4
34	2.69	54.8
35	2.78	56.6
36	2.69	54.8
37	2.72	55.4
38	2.65	54
39	2.36	48.2
40	2.58	52.6

5. Conclusion

Vocabulary is one of the three basic elements of language and plays an important role in language learning. Furthermore, language learning starts with vocabulary. This paper argues that the learning of English vocabulary is important for improving grammar, listening, reading, and writing. It is also conducive to deepening the cultural knowledge of English, which can promote the intellectual development of students. Adaptive vocabulary learning mode is an effective way to improve the students' vocabulary knowledge. In English vocabulary learning, the key to success is to focus on changing the learner's role and constantly strengthen the motivation to learn English vocabulary. It is necessary to increase the interest in learning English vocabulary and develop strategies for metacognition and vocabulary learning. In this way, it is not difficult to acquire English vocabulary self-study ability or develop the habit of English vocabulary self-study. The research on the English vocabulary adaptive learning model based on blockchain and deep learning is also of great significance for promoting the current scientific development.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

References

[1] F. Safara, "Autism spectrum diagnosis using adaptive learning algorithm for multiple MLP classifier," *Journal of Intelligent Systems and Internet of Things*, vol. 2, no. No. 2, pp. 33–44, 2021.

[2] M. Zhu, C. Li, S. Zhao, L. Chen, and X. Zhao, "The role of three-dimensional reconstruction of medical images and virtual reality in nursing experimental teaching," *Journal of Healthcare Engineering*, vol. 2022, Article ID 3853193, 13 pages, 2022.

[3] X. Wang and D. Zhang, "A study on the influence of computer corpus software on college students' English vocabulary learning," *International Journal of Emerging Technologies in Learning*, vol. 12, no. 08, p. 27, 2017.

[4] F. Ghaemi, "The impact of telegram as a social network on teaching English vocabulary among Iranian intermediate EFL learners," *International Journal of Information and Communication Sciences*, vol. 2, no. 5, p. 86, 2017.

[5] A. Tlili, S. Hattab, F. Essalmi et al., "A smart collaborative educational game with learning analytics to support English vocabulary teaching," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 6, no. 6, p. 215, 2021.

[6] M. Iansiti and K. R. Lakhani, "The truth about blockchain," *Harvard Business Review*, vol. 95, no. 1, pp. 118–127, 2017.

[7] J. J. Sikorski, J. Haughton, and M. Kraft, "Blockchain technology in the chemical industry: machine-to-machine electricity market," *Applied Energy*, vol. 195, no. JUN.1, pp. 234–246, 2017.

[8] N. Kshetri, "Can blockchain strengthen the Internet of things?" *It Professional*, vol. 19, no. 4, pp. 68–72, 2017.
[9] S. Olnes, J. Ubacht, and M. Janssen, "Blockchain in government: benefits and implications of distributed ledger technology for information sharing," *Government Information Quarterly*, vol. 34, no. 3, pp. 355–364, 2017.
[10] C. Pop, T. Cioara, M. Antal, I. Anghel, I. Salomie, and M. Bertoncini, "Blockchain based decentralized management of demand response programs in smart energy grids," *Sensors*, vol. 18, no. 2, p. 162, 2018.
[11] P. K. Sharma, S. Yeon Moon, and J. Hyuk Park, "Block-VN: a distributed blockchain based vehicular network architecture in smart city," *Journal of Information Processing Systems*, vol. 13, no. 1, pp. 184–195, 2017.
[12] P. K. Sharma, S. Singh, Y. S. Jeong, and J. H. Park, "DistBlockNet: a distributed blockchains-based secure SDN architecture for IoT networks," *IEEE Communications Magazine*, vol. 55, no. 9, pp. 78–85, 2017.
[13] M. H. Miraz and M. Ali, "Applications of blockchain technology beyond cryptocurrency," *Annals of Emerging Technologies in Computing*, vol. 2, no. 1, pp. 1–6, 2018.
[14] J. Chen, Z. Lv, and H. Song, "Design of personnel big data management system based on blockchain," *Future Generation Computer Systems*, vol. 101, pp. 1122–1129, 2019.
[15] A. K. Singh, A. Anand, Z. Lv, H. Ko, and A Mohan, "A survey on healthcare data: a security perspective," *ACM Transactions on Multimedia Computing, Communications, and Applications*, vol. 17, no. 2s, pp. 1–26, 2021.
[16] L. Lafta Jassim, "Methods for learning English vocabulary employed by Iraqi EFL learners at university of technology," *Arab World English Journal*, vol. 2, no. 2, pp. 314–328, 2021.
[17] M. K. Pattaralee Naenon and P. Naenon, "The use of board games to develop English vocabulary of ornamental and flowering plants sold in the community of primary 5 (grade 5) students at nikornradburana school, Thailand," *Psychology and Education Journal*, vol. 58, no. 1, pp. 1484–1489, 2021.
[18] M. E. Peck, "Blockchain world - do you need a blockchain? This chart will tell you if the technology can solve your problem," *IEEE Spectrum*, vol. 54, no. 10, pp. 38–60, 2017.
[19] R. T. Aune, A. Krellenstein, M. O'Hara, and O. Slama, "Footprints on a blockchain: trading and information leakage in distributed ledgers," *The Journal of Trading*, vol. 12, no. 3, pp. 5–13, 2017.
[20] M. Möser, K. Soska, E. Heilman et al., "An empirical analysis of traceability in the monero blockchain," *Proceedings on Privacy Enhancing Technologies*, vol. 2018, no. 3, pp. 143–163, 2018.
[21] S. Ghobadi, M. Shahrokhi, and A. Abedi, "Impact of ELSE game-based English vocabulary learning app on Iranian EFL exceptional students' vocabulary learning: EFL professionals and computer experts' evaluation in focus," *Machine Translation*, vol. 11, no. 2, pp. 149–173, 2021.
[22] O. I. Khalaf, G. M. Abdulsahib, H. D. Kasmaei, and K. A. Ogudo, "A new algorithm on application of blockchain technology in live stream video transmissions and telecommunications," *International Journal of e-Collaboration*, vol. 16, no. 1, pp. 16–32, 2020.
[23] a. admin, I. e. el-henawy, and K. Ahmed, "An improved equilibrium optimizer algorithm for tackling global optimization problems," *Fusion: Practice and Applications*, vol. 3, no. No. 1, pp. 01–28, 2021.
[24] M. Hammoudeh and S. M. Aljaberi, "Modeling of deep learning based intrusion detection system in Internet of things environment," *Journal of Cybersecurity and Information Management*, vol. 8, no. No. 1, pp. 17–25, 2021.
[25] K. Dilrabo, "Effective strategies and techniques of teaching English vocabulary," *Academicia: An International Multidisciplinary Research Journal*, vol. 11, no. 3, pp. 1454–1457, 2021.
[26] S. Chairani, "Using scrabble for learning English vocabulary at man 2 Kuantan Singingi," *Language Literacy Journal of Linguistics Literature and Language Teaching*, vol. 5, no. 1, pp. 205–212, 2021.
[27] F. Sadouki, "The influence of French on learning English vocabulary for L1 Arabic speakers: the case of secondary school students in Algeria," *European Journal of Teacher Education*, vol. 2, no. 1, pp. 179–189, 2020.