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Article

Advancing an ecological framework for English language teaching in web-based environments

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Abstract: As English language teaching (ELT) adapts to the digital age, web-based environments present new challenges for achieving an ecologically balanced instructional ecosystem. Applying an educational ecology framework, this study examines the structural and functional dynamics within web-based ELT, viewing the digital classroom as a biomechanical system where information flow, interaction forces, and adaptation mechanisms play crucial roles. By integrating Data Mining (DM) technology, the study evaluates ELT efficiency from an ecological standpoint, aiming to enhance both student engagement and learning outcomes through optimized instructional dynamics. Findings indicate that the applied algorithm achieves an accuracy of 95.27%, with system stability maintained above 90% under high parallel processing loads, demonstrating the robust performance of this approach. Ultimately, this paper contributes to the development of an ecologically balanced, web-based ELT model, supporting educators in creating adaptable, resilient digital learning environments.

Keywords: educational ecology; English language teaching; biomechanics of learning systems; Data Mining; digital instructional dynamics

1. Introduction

With the diversification of English language teaching (ELT) methods and approaches, there is growing attention on enhancing the quality of ELT. From the perspective of educational ecology, ELT represents an organic and complex ecosystem [1], shaped by external social environments and internal ecological balance. This ecosystem includes teachers, learners, resources, interaction mechanisms, management, and assessment systems [2]. Ecologicalization in teaching involves applying ecological theories and methods to integrate educational activities with their surrounding environments, balancing positive and negative educational influences to support the sustainable development of ELT. A primary goal of instructional level assessment is to evaluate the effectiveness of teachers and teaching organizations and to refine teaching practices, establishing guidelines for continuous improvement [3,4]. From an ecological perspective, educators should aim to create a harmonious, dynamic, and positively evolving ELT classroom ecosystem to restore and maintain ecological balance.

Data Mining (DM) is a powerful tool that leverages large data sets and various algorithms to extract meaningful insights [5]. Often, the data collected in educational settings is vast and complex, challenging traditional methods of analysis and limiting our ability to gain actionable insights [6]. This paper explores ELT level assessment through an ecological lens and proposes an assessment model based on DM algorithms. It also introduces optimization strategies for web-based ELT to foster supportive learning conditions and improve student efficiency.

The integration of computers into language teaching reflects evolving instructional theories and aligns with the growing demand for effective digital learning environments [7,8]. Traditional assessment systems in Chinese universities rely heavily on qualitative indicators, which can be difficult to manage systematically. In contrast, the classification methods within DM technology offer a more structured approach to address these challenges. By analyzing ELT level assessment from an ecological perspective and developing a DM-based assessment model, this study aims to enhance ELT practices, create conducive learning environments, and improve student learning efficiency. Informed by ecological principles, this paper also addresses current imbalances in web-based ELT, proposing strategies for ecological classroom development to improve instructional outcomes and optimize resource utilization.

A body of existing research provides insights into DM technology and its applications in educational assessment. For example, Al-Qallaf et al. introduced key DM methods and algorithms, comparing applications in instructional assessment across universities [9]. Li et al. highlighted association rule mining as a significant method within DM, especially frequent pattern mining [10]. Sheridan et al. integrated humanistic, constructivist, and interactive theories to develop a diversified ELT model that supports self-driven learning, e-interaction, cooperation, and cultural awareness [11]. Saito et al. employed decision tree algorithms to analyze teaching factors that influence university students' learning levels, illustrating the potential for instructional improvement [12]. Martin examined the integration of IT in college English writing, applying constructivist principles to design task-based instructional resources [13]. Liu explored self-directed learning models, analyzing student feedback, teacher interviews, and assessments to enhance learning outcomes [14]. Deng emphasized the importance of internal assessment for educational management, highlighting its role in raising educational standards to meet societal needs [15]. Xerri et al. noted the low adoption of high-tech resources in Chinese education, especially in resource development [16]. Hayashi et al. emphasized the role of "Internet + education" in modernizing ELT and supporting online learning expansion [17]. Sun et al. argued for the ecological reform of university foreign language courses as essential for innovation in ELT [18]. Yuan advocated for the integration of IT in traditional ELT, merging online and classroom resources [19]. Finally, Sun proposed an instructional assessment system using DM, outlining its objectives, functionality, and database design [20].

This paper introduces DM technology into ELT level assessment, with the goal of enhancing instructional quality and learning efficiency in web-based environments. Through a comprehensive analysis of DM's theoretical and practical applications, we employ DM algorithms to mine instructional assessment data, providing quantitative insights into the impact of various teaching factors on student learning. Key innovations include: (1) integrating DM technology with an ecological perspective on ELT to enhance students' learning outcomes; and (2) using DM algorithms to quantitatively assess instructional impact. The paper is structured as follows: an introduction to the background and significance of web-based ELT assessment, a review of related research, the theoretical foundation and construction of an ELT assessment model based on DM, verification of the model's effectiveness through simulation experiments, and a conclusion that highlights the study's contributions and suggests future research directions in ELT assessment.

2. Methodology

2.1. The construction of ELT ecosystem under the web environment

With the expansion of society, English language teaching (ELT) is undergoing significant changes in instructional philosophy, resources, methods, design, and resource utilization and development [21]. Learners' primary motivations and urgent needs for language learning are closely related to national language policies. However, there remains a gap between students' current learning conditions and the overall objectives of the new college English courses, as well as the specific goals of these courses. Although many universities have integrated the Internet into ELT, some teachers are not fully leveraging its advantages, often assigning students to independent study without sufficient supervision. This lack of oversight makes it challenging to ensure that students complete their English studies independently.

Eco-foreign language teaching emphasizes the interaction between teachers and students within both the material and humanistic environment. This approach views all elements in the foreign language classroom as components of a comprehensive ecosystem, wherein these factors are interdependent and mutually restrictive, often presenting pairs of contradictions. From an educational ecology perspective, the ELT ecosystem can be seen as an organic and complex system, comprising both biotic (teachers, learners) and abiotic factors (resources, management, and assessment mechanisms). These elements, though distinct, are interconnected and collectively form the overall environment for English learning.

In a web-based environment, ELT aligns with the principles of educational ecology by advocating a learner-centered approach. While teachers play a crucial role, the emphasis is on empowering students as active participants in their learning. The shift to digital environments has disrupted the traditional ELT classroom balance, resulting in four types of imbalances: (1) material environment imbalance; (2) environmental imbalance; (3) technological environment imbalance; and (4) emotional environment imbalance. Since ELT is closely linked to its surrounding environment, establishing an ecological instructional model within the web environment requires attention to the connections with this environment to improve the ecological quality of ELT.

Universities should consider providing optimal learning conditions. Beyond constructing diverse school buildings, classrooms should be designed to meet students' varied needs, including multimedia classrooms that offer a quiet, comfortable, and well-connected learning environment. ELT and its ecosystem interact and depend on each other, forming a complete educational ecosystem. Within the ELT system, external environmental factors also interact and influence one another, collectively guiding the development of the entire college education system.

The network resource environment comprises three components: hardware resources, information resources, and learning resources. Hardware resources facilitate convenient interaction mechanisms for learning, while information resources provide diverse, accurate language input via the Internet. Learning resources include systematic learning packages, software, and courseware tailored to different learning levels, enhancing the overall learning experience. Teachers must integrate textbook content effectively and improve students' understanding to help them adapt to web-based ELT.

Web-based ecological ELT represents an inevitable trend in ELT reform, characterized by personalized, interactive, and collaborative teaching and learning conditions. As students interact with learning media, resources, and peers, their emotional and psychological states significantly impact the learning process. For students, learning in a digital environment involves not only cognitive development but also emotional responses that influence their cognitive growth. Universities should establish a robust system for multimedia network training for English teachers, with specific measures such as scheduled training sessions during winter and summer breaks, certification upon completion, and inviting experts for lectures on the latest network theories. These training sessions should be strictly implemented and tailored to meet the diverse needs of English teachers.

The construction of an ELT ecosystem in a web environment can be approached from several angles:

The ELT ecosystem should align with the overall objectives of ELT talent development, emphasizing diversity and practicality.

A hybrid teaching model combining multimedia classroom instruction with autonomous online learning should be established for courses such as Business English writing.

The traditional reliance on summative assessment should be reformed, combining formative and summative assessments to evaluate students' learning outcomes more comprehensively. Online language resources not only provide up-to-date language content but also enhance learners' motivation by offering authentic cultural information from target language countries, closely aligning with learners' needs and supporting innovative instructional methods.

As an ecosystem, the English classroom thrives on the dynamic interaction of its ecological factors. Modern educational concepts emphasize harmonious teacher-student relationships and effective communication. Therefore, to improve the ecological ELT model in a web environment, it is essential to strengthen teacher-student interaction. In ELT, managing these relationships effectively allows classroom teaching to reach ecological optimization and supports students' holistic development. Balanced interactions between teachers and students, students and peers, and students and technology are vital for a healthy and dynamic learning ecosystem. Additionally, integrating computer networks into the curriculum demands not only strong teacher-student interactions but also effective interactions with digital tools.

2.2. DM technology

For example, identifying the general characteristics of data and predicting development trends are tasks that traditional management systems struggle to perform. This is where Data Mining (DM) technology becomes invaluable. Applying DM to educational administration allows us to uncover inherent patterns within data, which, when applied to educational management, can foster instructional innovation and improve school operations and management practices.

On a commercial level, DM serves as an information processing technology. Its primary function is to extract, transform, analyze, and process business data, providing essential support for making informed decisions through data modeling and processing. One of DM's key objectives is to make hidden patterns within data accessible and understandable for users.

To effectively use DM technology to extract useful information, data must be pre-processed and thoroughly analyzed. The entire process, from preparatory work to result analysis, is referred to as a DM project, with the implementation of a DM project following a structured process. The DM environment and steps involved in this process are illustrated in **Figure 1**.

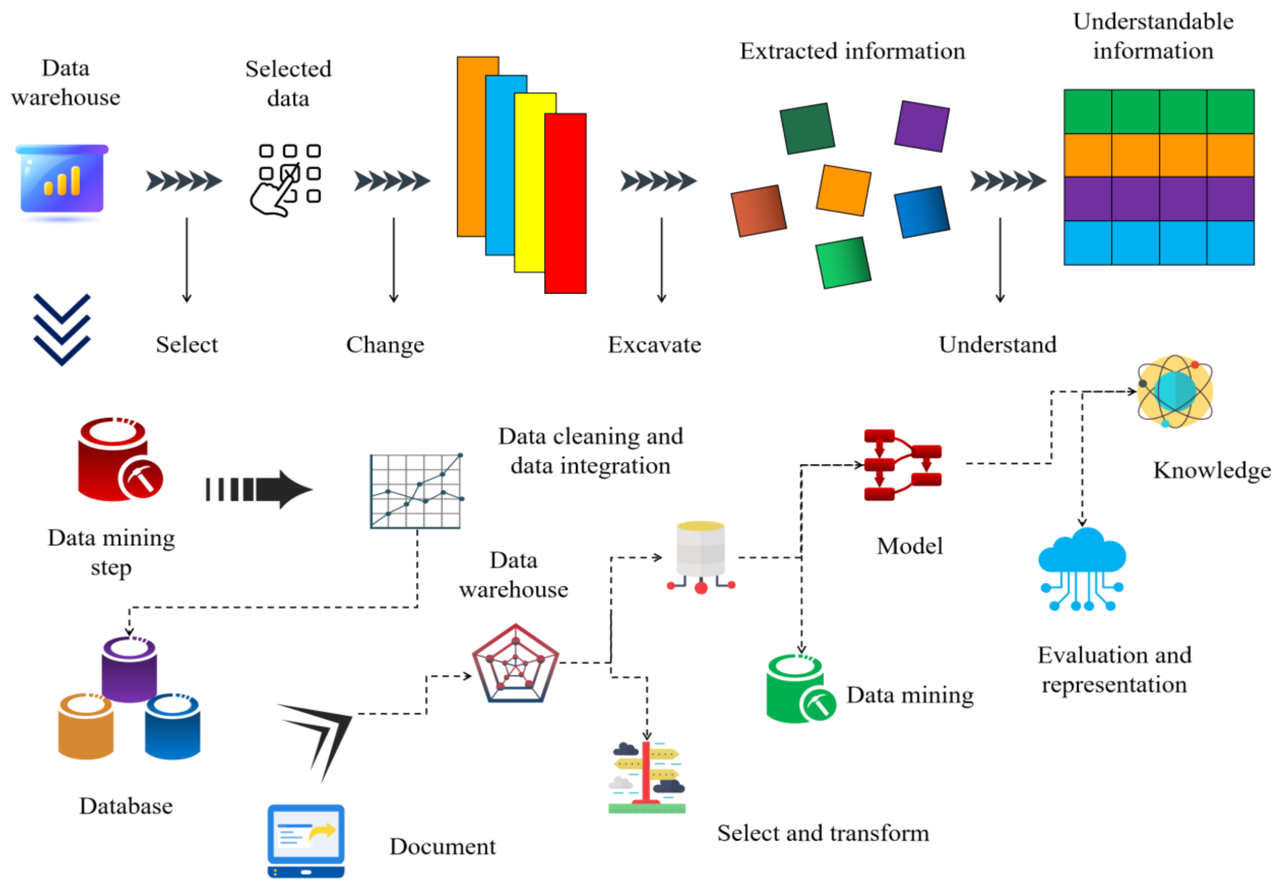

Figure 1. The environment and steps of DM.

Generally speaking, the tasks of DM are mainly divided into two categories, namely descriptive DM and predictive DM. Descriptive DM task is to describe the general characteristics and properties of data information. DM is to use DM tools and techniques to analyze the converted data, search or generate a specific interesting pattern or a specific data set. According to the task objectives of DM, the parameters of the corresponding algorithm are selected, and the data are analyzed to obtain the possible pattern models. The existing assessment indexes mostly adopt the comprehensive assessment method, and its index system usually consists of multi-level indexes. According to the role and guidance of these indicators in classroom instructional level, they are given different weights, forming a complete index system. However, these traditional instructional level assessment methods still have some defects. In this paper, DM technology is introduced into ELT level assessment, and based on comprehensive analysis of various data technologies, DM algorithm is used to effectively mine the instructional level assessment data set under the web environment.

2.3. ELT level assessment

Instructional level assessment is a key indicator of school instructional quality and serves as an essential tool for self-monitoring the effectiveness of ELT (English language teaching). Traditional assessment systems are often subjective and limited in scope. Establishing and implementing a scientific and objective assessment system for instructional levels is crucial for strengthening instructional management. A primary challenge in the demand analysis phase is identifying the aspects of instructional assessment that are suitable for Data Mining (DM) technology, which traditional assessment methods struggle to address.

Currently, instructional level assessment in universities relies on multiple factors. Typically, an instructional level assessment system includes components such as assessment methods, organizational structure, assessment index system, statistical processing of assessment data, and feedback of assessment results. By assigning appropriate assessment indices and weights to each component, the system can produce a relatively fair and unbiased outcome, providing valuable feedback for teachers to improve and optimize their instructional practices, ultimately enhancing student learning experiences.

The process for assessing the ELT ecosystem's instructional level within a web-based environment is illustrated in **Figure 2**.

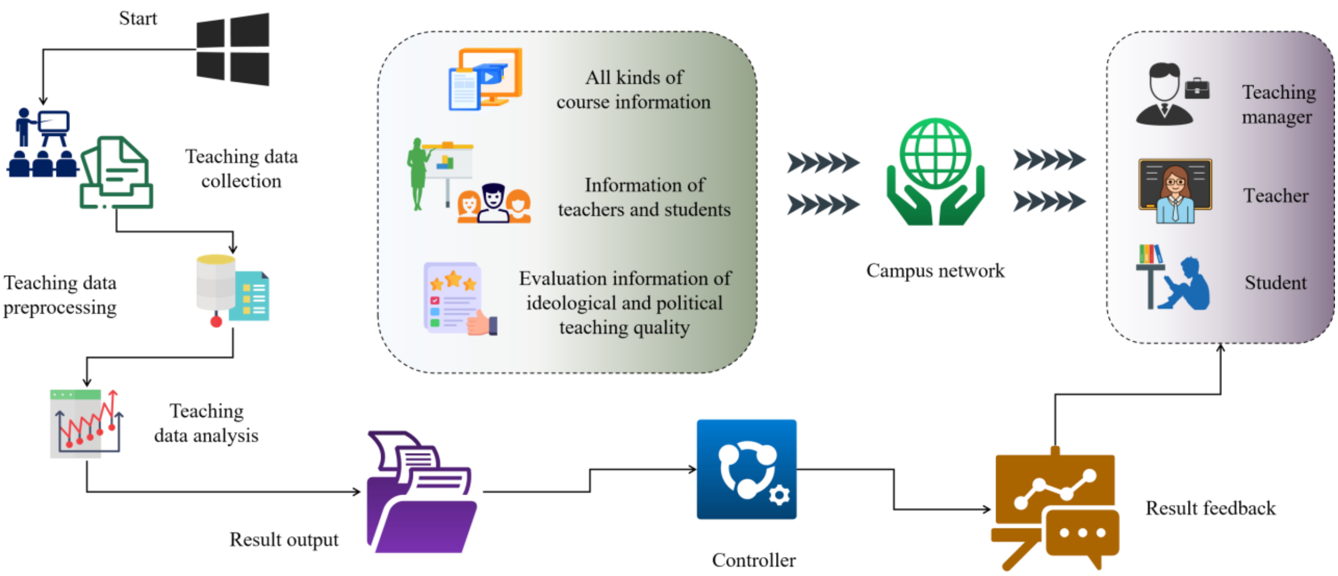

Figure 2. Assessment process of ecosystem ELT level under web environment.

Firstly, this paper preprocesses the data and extracts useful information data to form mining objects. Then, the code table is converted into a transaction database, the frequent item set is generated by Apriori algorithm according to the given minimum support and confidence, the mining association rules are generated according to the given minimum confidence, and then the mining results are displayed in table form, and the corresponding data reports are generated. Feature processing is one of the key steps to solve DM work by using machine learning model, which plays a very important role in DM work and is a process of mining effective information from a great quantity of data sets. The main methods of feature processing are normalization, discretization, feature dimension reduction and feature selection.

Let the support of the $I_1 \subseteq I$ item set I_1 on the data set D be the percentage of transactions containing I_1 in the D, namely:

$$Support(I_1)\frac{\|\{t \in D\}|I_1 \subseteq I|\|}{\|D\|} \tag{1}$$

In the formula, $\|\cdot\|$ represents the quantity of elements in the set. On I and D, association rules in the form of $I_1 \Rightarrow I_2$ are defined by satisfying a certain degree of credibility, trust or confidence. The so-called credibility of a rule refers to the ratio of the quantity of transactions including I_1 and I_2 to the quantity of transactions including I_1, that is:

$$Confidence(I_1 \Rightarrow I_2) = \frac{Support(I_1 \cup I_2)}{Support(I_1)} \tag{2}$$

Numeric association rules can also contain categorical variables. Let T be the set of t data samples. Suppose the target class attribute has m different values, namely:

$$\{C_1, C_2, C_3, \dots, C_m\} \tag{3}$$

Let S_i be the quantity of samples in class C_i. The information entropy required to classify a given sample is:

$$Info(T) = -\sum_{i=1}^{m} p_i \log_2(p_i) \tag{4}$$

Among them, A p_i is just the probability that any sample belongs to the C_i. Usually, the logarithmic function is base 2, so the entropy is in bits. According to the information entropy divided into subsets by X is:

$$Info_x(T) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} Info(T_i) \tag{5}$$

where the term $|T_i|/|T|$ acts as a weight for the i th subset and is equal to the quantity of samples in the subset divided by the total quantity of samples in the T. The smaller the entropy value, the higher the purity of the subset division. Where, for a given subset T_i:

$$Info(T_i) = \sum_{j=1}^{m} \frac{T_{ji}}{T_i} \log_2\left(\frac{T_{ji}}{T_i}\right) \tag{6}$$

where the term T_{ji}/T_i is the probability that a sample in the T_i belongs to the target class C_j. Then the information gain on the X branch is:

$$Gain(X) = Info(T) - Info_x(T) \tag{7}$$

Assuming that there are n training samples, the probability of occurrence of each sample conforms to the Bernoulli distribution, and $p(y_i = 1|x_i)$ represents the probability of occurrence of positive class, then the probability of occurrence of negative class is:

$$1 - p(y_i = 1|x_i) \tag{8}$$

For each sample, the posterior probability is:

$$p(y|x, w) = p(y_i = 1|x_i)^{y_i}\big(1 - p(y_i = 1|x_i)\big)^{1-y_i} \tag{9}$$

So the maximum likelihood function of the sample is the posterior probability product of each sample, namely:

$$L(w) = \prod_{i=1}^{m} p(y_i = 1|x_i)^{y_i}\big(1 - p(y_i = 1|x_i)\big)^{1-y_i} \tag{10}$$

Log likelihood function:

$$l(w) = \sum_{i=1}^{m} \log p\,(y_i = 1|x_i)^{y_i} + \log\big(1 - p(y_i = 1|x_i)\big)^{1-y_i} \tag{11}$$

Expand it and solve it, and take the derivative of w:

$$\frac{\partial l(w)}{\partial w} = \sum_{i=1}^{m}\big(y_i - g(z)\big)x_i \tag{12}$$

Based on the classic Apriori, this paper adopts a new data structure, and the improved algorithm plans to adopt a data structure based on linked list. In this way, multiple scans of the database in Apriori algorithm can be avoided, a lot of I/O overhead can be reduced, and the performance of the system can be greatly improved. This system has the advantages of low investment, easy maintenance and strong practicability. The extraction strategy provided by the system mainly includes: determining the quantity of records to be extracted, the starting position of extraction, and whether arithmetic progression extraction is random extraction. The general practice of feedback of assessment results is that the academic affairs office collates the assessment results and feeds them back to teachers through certain channels, and at the same time, the results are fed back to the management as the basis for rewards, policies and measures. Ordinary teachers should have the right to evaluate themselves and other teachers, while teaching administrators have the right to modify, query and view DM results.

3. Result analysis and discussion

Visual Studio is used as the system development tool, with Microsoft SQL Server serving as the backend database development tool, and the Windows operating system as the development environment. The system is designed to operate in a Browser/Server (B/S) model, a well-established development approach. This system employs a three-tier architecture, consisting of the presentation layer, business layer, and data layer.

The presentation layer is on the client side, providing users with an interactive interface and displaying feedback.

The business layer runs on the server, responsible for analyzing client requests, processing them, and returning the results to the client.

The data layer handles data storage, comprising the basic database, mining database, and knowledge base.

One of the main challenges in implementing Data Mining (DM) applications is data preparation. Instructional assessment data are often scattered across various materials, making it difficult to locate or occasionally contradictory. Additionally, some essential data are either overlooked by the management department or do not exist, creating further challenges for system testing.

A critical step in DM preparation is data preprocessing, as well-preprocessed data significantly enhance the quality of DM results, making the mining process more accurate and efficient. **Table 1** presents the index weights used in the instructional level assessment system.

Table 1. Weights of instructional level assessment system indicators.

Method	Student assessment	Peer review	Expert appraisal	Self-assessment
Analytic hierarchy process	0.489	0.158	0.269	0.085
Expert opinion averaging method	0.365	0.193	0.281	0.152
Average value	0.431	0.178	0.276	0.128
Final weight	0.398	0.215	0.304	0.098

High-dimensional data may contain redundant information, potentially concealing important relationships. Dimension reduction becomes necessary to eliminate redundancy, reduce the volume of data to be processed, and decrease model complexity, ultimately improving the accuracy of learning outcomes. In the instructional assessment system presented in this paper, the assessment process is organized based on distinct assessment objects:

Student assessment occurs at the end of the course.

Peer assessment is conducted at the end of the teaching task.

Supervision assessment records results at the end of the term.

Self-assessment is performed simultaneously with peer assessment.

These assessments focus on various aspects—teaching attitude, teaching content, instructional methods, and instructional effectiveness. Mode integration is applied to verify if the assessment data across these categories are consistent. The instructional assessment data include fundamental information on teachers, course details, class sessions, and basic student information. Reducing data redundancy as much as possible is essential for providing high-quality data to the Data Mining (DM) process. **Figure 3** illustrates the training process for this algorithm.

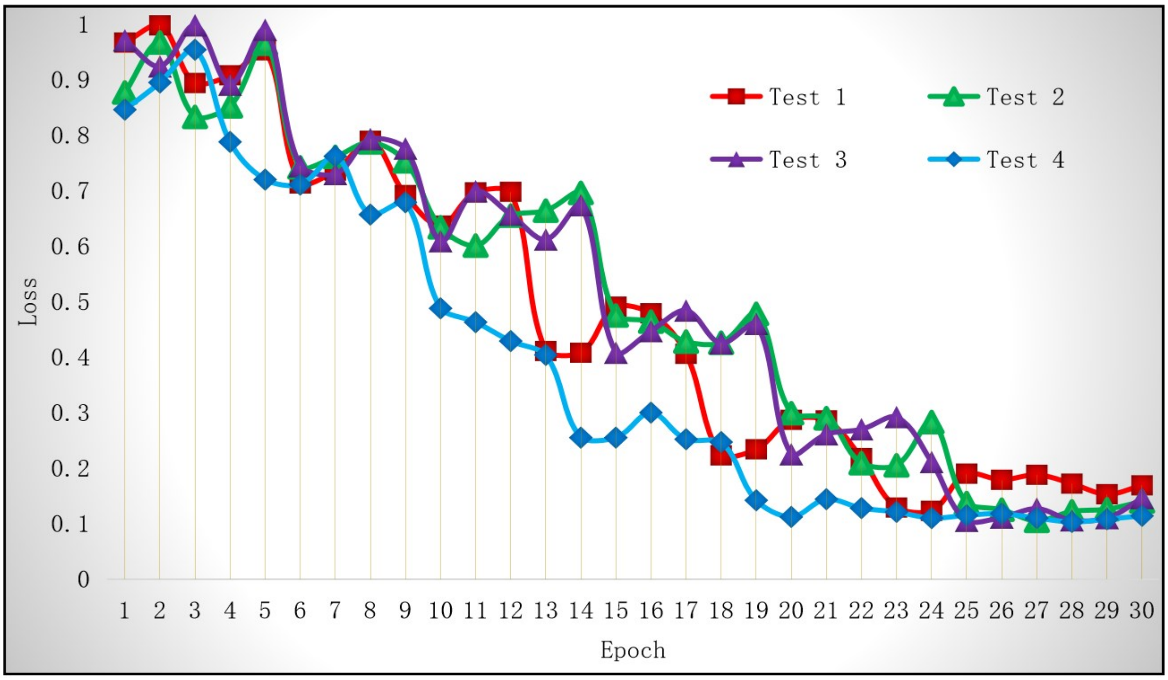

Figure 3. Training of the algorithm.

In this paper, the divergence of each dimension feature is calculated. For example, by calculating the variance of each dimension feature, if its variance value is equal to or close to 0, it means that this feature is not helpful for sample division when participating in model training. By analyzing the features and eigenvalues of each dimension, the non-divergent features are screened out, and these non-divergent features are removed during model training. In addition, DM system of instructional assessment provides the functions of decision tree generation and data prediction. The generation of decision tree is used to generate decision tree model and rule set from training data, and data prediction is used to classify and predict unknown data. In this paper, accuracy, error and running time are selected to verify the performance of the algorithm. **Figure 4** shows the accuracy of the algorithm. **Figure 5** shows the error of the algorithm. **Figure 6** shows the running time of the algorithm.

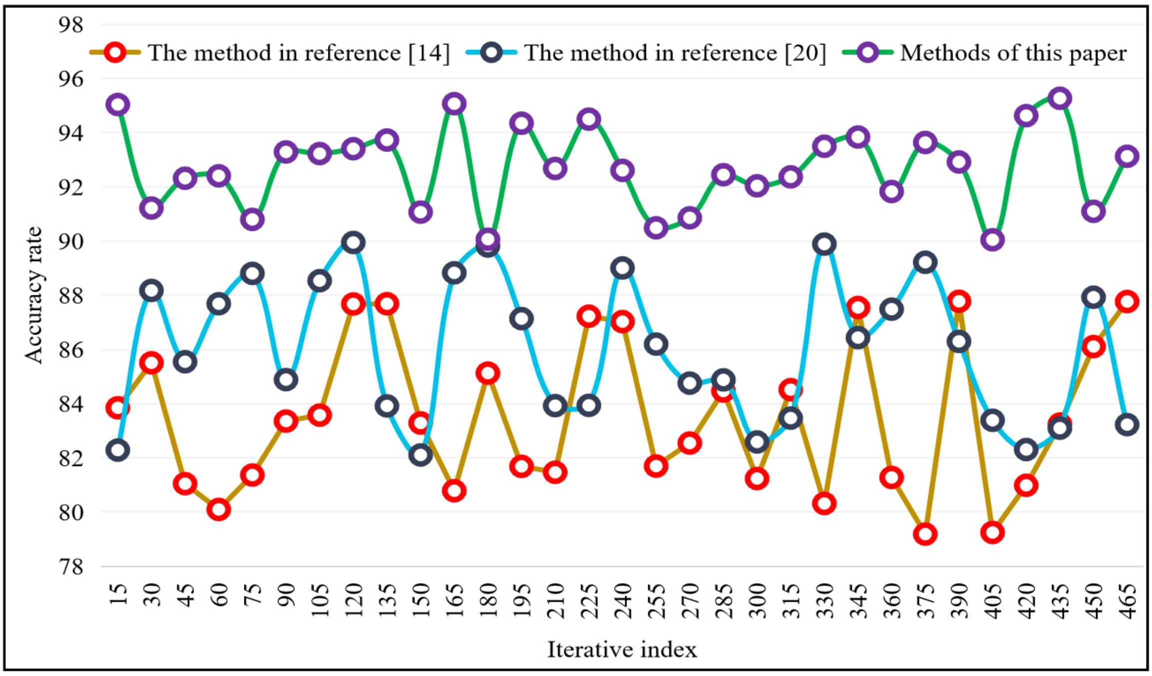

Figure 4. Accuracy of the algorithm.

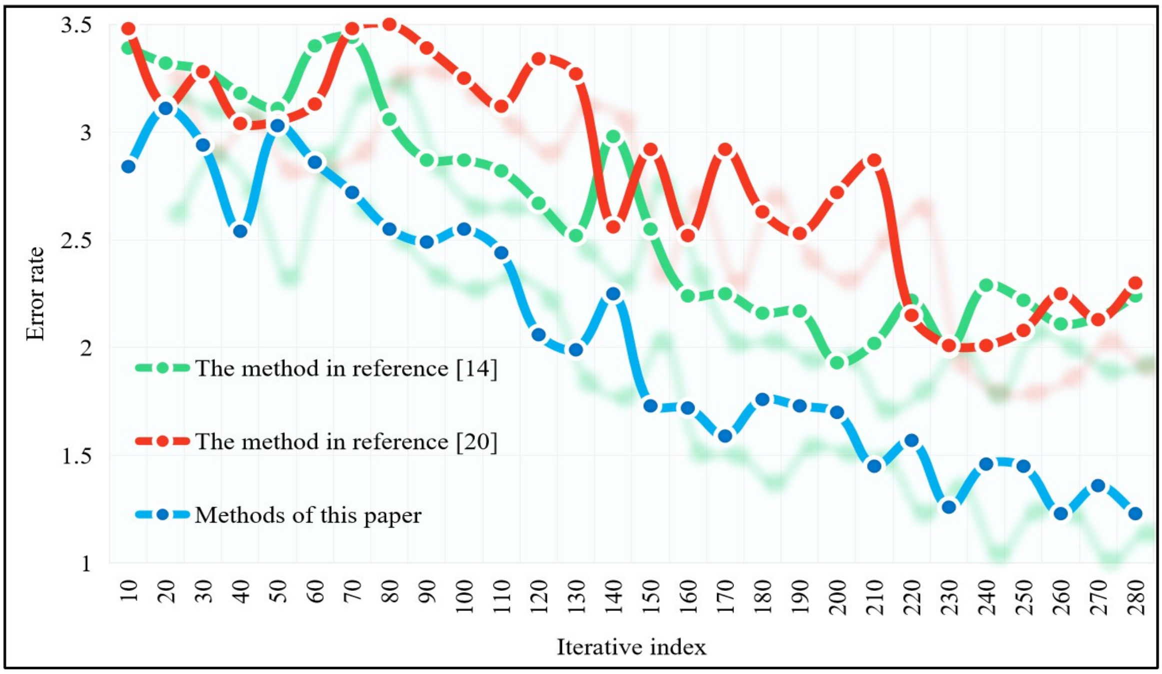

Figure 5. Error of the algorithm.

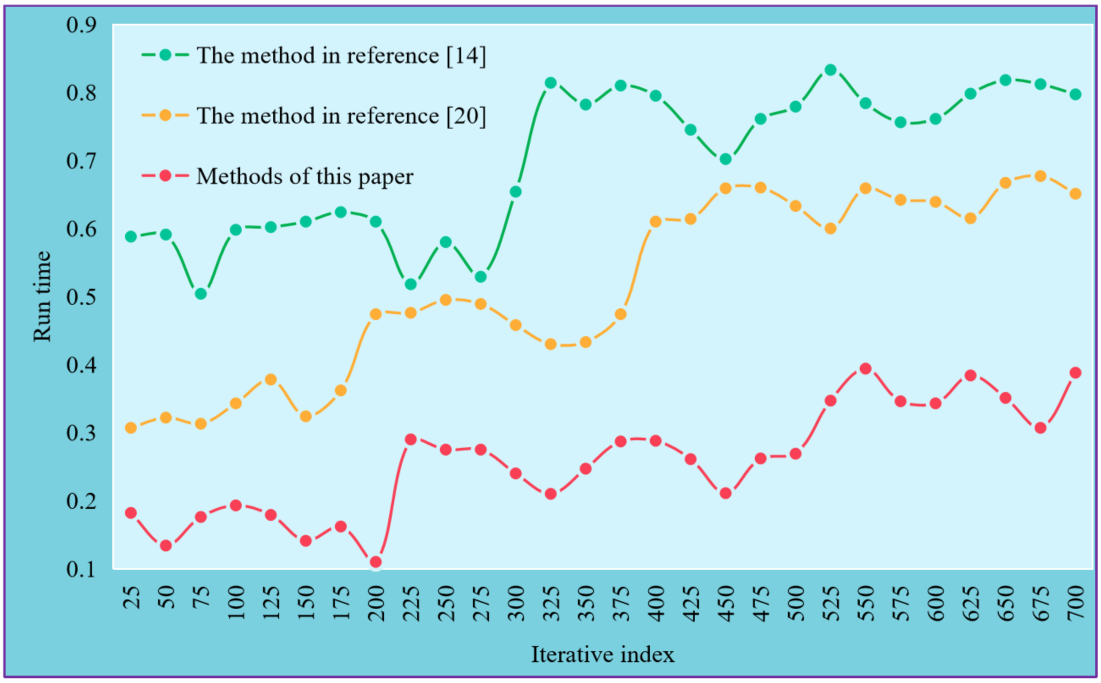

Figure 6. The running time of the algorithm.

At the same time, this paper mines the instructional assessment data, and some results are shown in **Table 2**.

Table 2. Association rule mining results.

Rule	**Age**	**Professional title**	**Academic degree**	**Teaching attitude**	**Teaching content**	**Teaching method**	**Teaching effect**	**Support (%)**	**Confidence (%)**
1	A1							31.5	16.2
2	A2							31.9	43.5
3	A3							12.4	37.4
4	A4							16.2	14.1
5		J3						60.8	80.5
6		J2						13.2	32.8
7		J1						15.9	11.9
8			E2					35.8	76.6
9			E1					55.4	24.1
10				T1				37.2	19.6
11				T2				21.3	13.2
12				T3				11.7	4.97
13					C1			52.8	64.3
14						M1		45.6	31.5
15						M2		33.2	13.6
16						M3		46.1	53.9
17							R1	31.4	28.8
18							R2	22.9	24.1

Each rule in the system includes the following components: a unique rule number to identify the rule, one or more conditions, the classification derived after satisfying these conditions, and the rule's confidence level, represented numerically. Assessing instructional level is a complex task that requires consideration of numerous influencing factors across multiple levels. An assessment set directly describes a teacher's instructional level based on specific assessment indices.

In this paper, association rules within Data Mining (DM) are applied to mine and analyze both historical and current instructional assessment data. This analysis helps identify the factors impacting teachers' instructional effectiveness, enabling teachers to recognize and address areas for improvement, thereby enhancing their instructional level. Additionally, this approach provides schools with a comprehensive analysis of instructional levels. The system's stability is depicted in **Figure 7**.

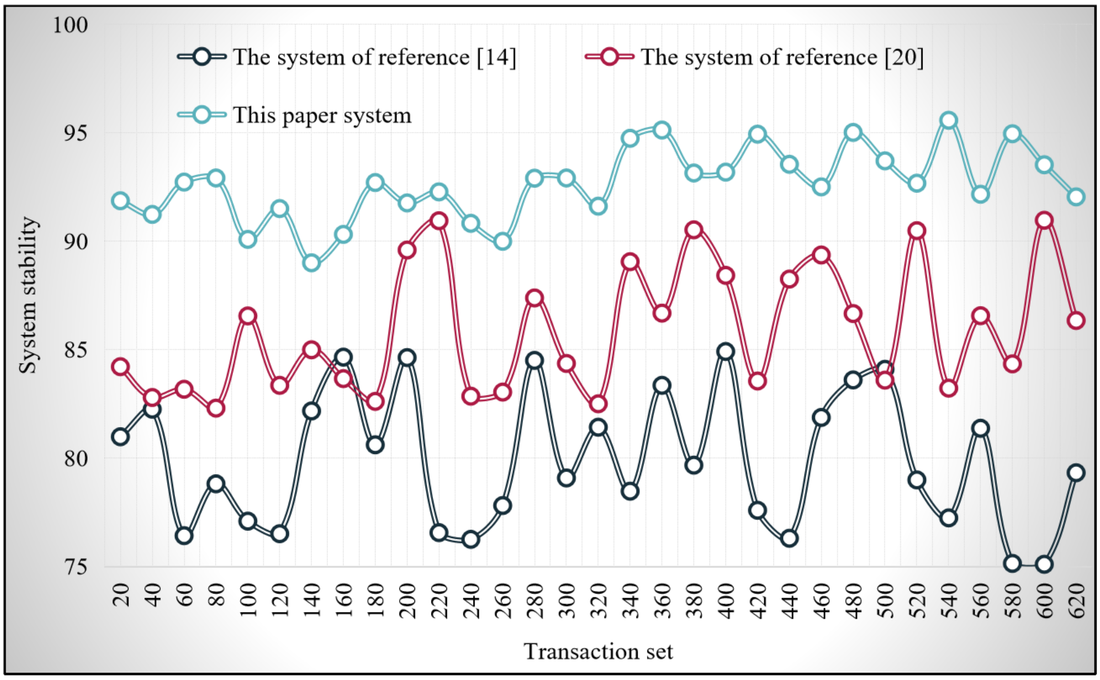

Figure 7. Stability of the system.

The results show that the algorithm achieves an accuracy of 95.27% and demonstrates excellent system stability. Even under high parallel processing loads, system stability remains above 90%, reflecting robust performance. Additionally, the partition-based algorithm proposed in this paper requires only two scans of the database, significantly accelerating I/O operations, saving time, and improving overall efficiency. This approach also optimizes space utilization in the Data Mining (DM) process.

4. Conclusions

English language teaching (ELT) in a web-based environment differs significantly from traditional learning conditions, with unique characteristics that offer both opportunities and challenges. Web-based ELT provides a classroom environment that transcends time and space, enhances the convenience and engagement of English learning, meets diverse student interests and needs, and fosters greater student participation. However, while digital networks open new avenues for teaching, they also demand higher standards for effective ELT implementation. Integrating information technology into ELT has a notable impact on maintaining the ecological balance within this teaching mode. Therefore, exploring the role of IT in ELT is crucial for establishing a healthy and mature ecological ELT model.

This paper addresses the current imbalances in web-based ELT and proposes strategies for constructing an ecologically balanced classroom. By integrating Data Mining (DM) technology, the study evaluates ELT effectiveness from an ecological perspective, aiming to improve students' learning efficiency and overall outcomes. The research demonstrates that the applied algorithm achieves an accuracy of 95.27% and maintains system stability above 90% even under high parallel processing demands, reflecting its strong performance.

Looking forward, it is essential to develop customized ELT models for different universities, tailoring the approach to their specific needs. This will optimize the benefits of web-based ELT and support the expansion of quality education reform across universities.

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Conflict of interest: The author declares no conflict of interest.

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