

Retraction

Retracted: Construction of the EFL Mobile Learning Model in the Hybrid Distributed Terminal

Security and Communication Networks

Received 26 December 2023; Accepted 26 December 2023; Published 29 December 2023

Copyright © 2023 Security and Communication Networks. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Qu, S. Song, and Z. Xiao, "Construction of the EFL Mobile Learning Model in the Hybrid Distributed Terminal," *Security and Communication Networks*, vol. 2022, Article ID 4429174, 10 pages, 2022.

Research Article

Construction of the EFL Mobile Learning Model in the Hybrid Distributed Terminal

Lijie Qu ^{1,2,3}, Shihui Song,² and Zuochun Xiao³

¹School of Foreign Languages and Literature, Shandong University, Jinan 250100, China

²Construction Supervision Department, Suzhou Industrial Park, Suzhou 215000, China

³Shandong Lanshi Education Technology Co., Ltd, Jinan 250100, China

Correspondence should be addressed to Lijie Qu; qulijie@sdu.edu.cn

Received 25 October 2021; Revised 22 November 2021; Accepted 11 December 2021; Published 12 January 2022

Academic Editor: Jian Su

Copyright © 2022 Lijie Qu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the integration of technology in higher education, mobile learning plays an important role in EFL classes. In order to optimize the efficiency of EFL learning, a mobile learning model in the hybrid distributed terminal is constructed. The online platform supporting both synchronous and asynchronous learning with three types of interaction helps build a blended learning model and creates a closed loop for ubiquitous online and offline learning with multiple evaluation, which also builds a community of inquiry-based learning to facilitate collaborative study and deep thinking. Aiming to improve the resource scheduling performance of learning information sharing mode, based on the traditional sharing mode hardware, the mobile learning software for the hybrid distributed terminal is thus optimized. Learning resources are mined and fused to realize the scheduling of learning information resources, and user interface management function is designed to construct the EFL mobile learning mode with the hybrid distributed terminal.

1. Introduction

Computer network technology has a great impact on higher education, which has brought about new teaching methods, different kinds of interaction between teachers and students, and construction of multityped coursebooks. Technology makes videoconferencing, video broadcasts, or webcasting for distance learning become reality [1]. Mobile learning, or M-Learning with hybrid distributed terminals, is also developed with the emerging new technology in education, which allows learners to access anywhere and at any time.

In order to further optimize EFL (English as a foreign language) teaching with the integration of technology, some current research has yielded constructive research results. Some suggest using POA (production-oriented approach) theory as a guide, by integrating with technology and scientifically allocating the input of resources to promote students' autonomous learning, to enhance the output of learners, hence construct the intelligent teaching mode of College English, and ensure the effective linkage between

teaching and learning [2]. Some use the scientific measurement software CiteSpace to draw the dynamic evolution map of the integration of modern technology (multimedia technology, network environment, mobile learning, and ubiquitous learning) with foreign language teaching. The study covers 34 research hotspots such as autonomous learning, information technology, mobile learning, and classroom teaching. It found that the deep integration of information technology and foreign language education has a profound impact on foreign language learning style and the relationship between teachers and students, hence making open, free, and personalized foreign language learning possible [3].

However, the above learning models and research do not touch on the efficient mining of learning resources and user interface management function design which are supposed to optimize students' attendance and performance in application. This paper is intended to explore the construction of EFL mobile learning with the hybrid distributed terminal by building a blended learning mode and creating a community of inquiry-based learning.

2. Construction of the English Mobile Learning Model with the Hybrid Distributed Terminal

2.1. Online Platform Selection. With the continuous development of network information technology, a great amount of educational institutions and departments pay much attention to online teaching and select the most suitable and outstanding online teaching platform through continuous big data screening and observation [4, 5]. On the one hand, according to the teaching characteristics of colleges and universities and the needs of teachers and students, some might select the most suitable online teaching platform, while some tend to develop a suitable teaching platform and improve it by collecting data and feedback.

In view of the teachers' and students' needs and the characteristics of EFL courses, we use the hybrid distributed terminal software to construct the intelligent online teaching platform. This platform provides multityped teaching resources and a personalized and friendly teaching and learning mode, so that teachers and students may experience simplified, convenient, and high-quality teaching and learning services. On the platform, teachers can follow instructions to create courses for the target students, that is, SPOC (Small Private Open Course), and upload teaching resources such as supplementary course materials, quizzes, videos, micro lectures, class slides, and homework [6, 7]. It may also assist teachers in disciplining students, such as the exact time students join in, the number of times they are late, and determining the exact number of students who sign in by setting different gestures or scanning the QR Code, thus improving students' participation and engagement. The teaching platform user interface is shown in Figure 1.

In this way, both a synchronous and an asynchronous learning mode is constructed with effective interaction between students and teachers, students and students, and students and contents as well [8, 9]. Compared with traditional offline teaching, the platform is not restricted by location and time and is open to teachers and students as well as other self-learning users for free [8, 9]. Secondly, the platform is not limited to mobile phone but also compatible with PC, web pages, and official accounts [10]. It is more user-friendly and multifunctional regarding the uploading of teaching materials and micro lectures, quizzes, and posting of discussion, and comments on peers. Students' usage data provided by the platform will enable teachers to make evaluation more authentic and comprehensive and adjust teaching style and teaching contents accordingly.

2.2. A Closed Loop for Blended Learning. Blended learning is the combination of traditional F2F learning and distributed learning with the assistance of modern technology [11]. Blended learning has increased access and flexibility, and students are self-paced for the online part. Teachers should pay more attention to the relation between content, learners, and technology. They should adjust instructional methods and lesson design and use multityped teaching materials and activities to facilitate effective real-time interaction between teachers and students, students and students, and students

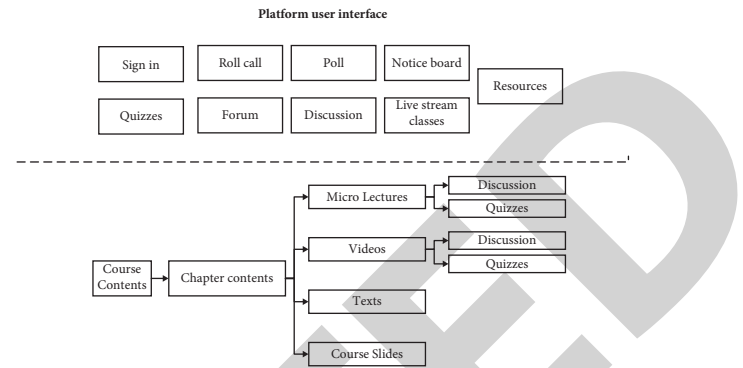


FIGURE 1: Platform user interface.

and contents to create the omnipresent learning environment of preclass, in class, and post-class. This model allows teachers to focus on more higher-order thinking activities such as group projects and group discussions to combine both individual and collaborative study. Accordingly, equal importance should be attached to peer evaluation, teacher evaluation, and self-evaluation which can be conducted in both online and offline modes. Therefore, a closed loop for blended learning is created which is demonstrated in Figure 2.

2.3. Creating the Community of Inquiry-Based Learning. The blended learning model enables teachers to build the community of inquiry-based learning with the hybrid distributed terminal, which cultivates deep thinking and collaborative learning.

At the onset of the semester, one class of students are divided into 6 groups with 5 members in each on the learning platform. They will conduct both individual and collaborative study. Compared with other activities like group discussion and group project, academic reading circles are designed to combine both individual and collaborative study, especially the facilitation of deep learning. In ARC, it starts with a text students are required to read, and students are assigned with different roles (group leader, highlighter, contextualizer, connector, and visualizer) and responsibilities to break up a text into 5 different aspects and analyze individually (Table 1) [12]. After that, learners meet and discuss on this platform with hybrid distributed terminals to share what they have found from the above-mentioned five perspectives (Figure 3). At face-to-face class, there will be volunteers and some will also be randomly chosen by roll call via this platform to demonstrate their part of work, and teachers will give them constructive and specific feedback. Roles will be rotated for the rest of the semester to guarantee each has fulfilled all roles.

Thus, a community of inquiry-based learning is constructed. In this community, students are learning by teaching in the flipped classroom, which has higher retention rates and facilitates deep learning [13–15]. In this community, students with higher English level will function as scaffolding for other group members to reduce their stress.

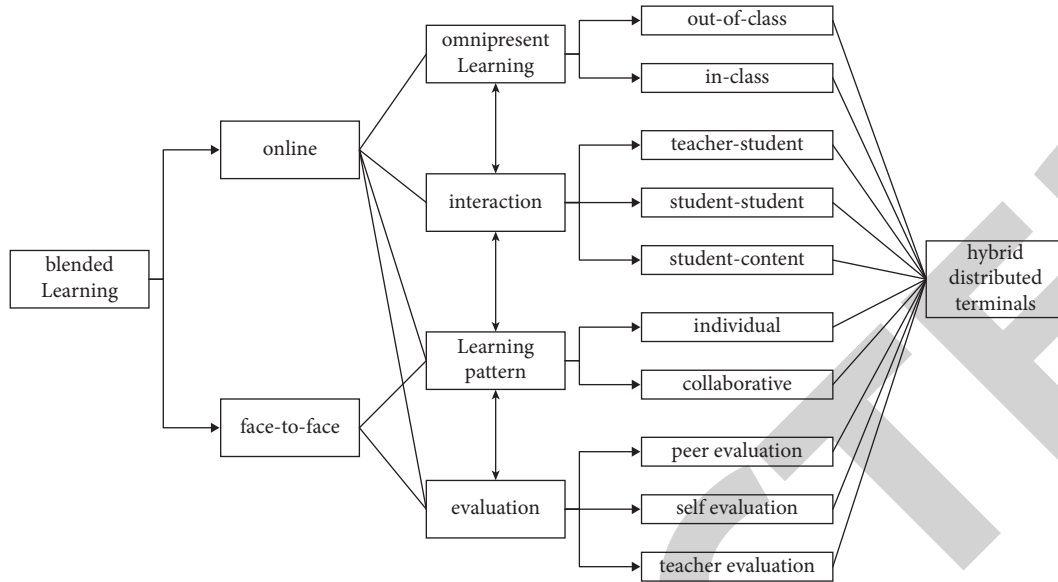


FIGURE 2: A closed loop of blended learning.

TABLE 1: Inquiry-based learning of ARC (academic reading circles).

Group serial number	Number of people	Score	Roles	Tasks
1-6	5	0-10 points	Group leader Highlighter Contextualizer Visualizer Connector	Ask comprehension questions requiring skimming and scanning, inferring, and critical thinking for the group to discuss. Lead the group to achieve mutual comprehension and ensure all members participate in group discussion and demonstration. Elaborate on lexical items, including new and topical vocabulary, and tonal language suggesting hedging or bias. Provide synonyms, explanations, or pictures to help classmates understand the words. Research 2 items about the background information, for example, the people, place, and events mentioned in text. Demonstrate key terms about the text visually in informatics. Relate 3 ideas in the text to other texts you have read or related to previous personal experience.

2.4. Big Data Mining and Fusion of English Mobile Learning Resources for the Hybrid Distributed Terminal. Aiming to improve the resource scheduling performance of learning information sharing mode, the overall optimization design of mode software is carried out on the basis of traditional sharing mode hardware.

2.4.1. Learning Resources Mining. In order to realize the sharing of English mobile learning information in the hybrid distributed terminal, a model of English mobile learning information detection and resource distributed fusion in the hybrid distributed terminal is established based on the big data mining and feature fusion method of English mobile learning information in the hybrid distributed terminal. The statistical data mining and fuzzy feature detection methods are adopted to schedule the decision-making and self-adaptive optimization of English mobile learning information in the hybrid distributed terminal [16, 17]. By subspace fusion clustering analysis, a multidimensional sample

detection model for English mobile learning information in the hybrid distributed terminal is established. The parameter set of English mobile learning information scheduling in the hybrid distributed terminal is obtained through decision function scheduling and fusion feature analysis. The management decision and integrated scheduling of English mobile learning information in the hybrid distributed terminal are carried out to improve the management capability of English mobile learning information in the hybrid distributed terminal [18]. The function of position optimization of English mobile learning information in the hybrid distributed terminal is as follows:

$$D(x, y) = \sum_{i=1}^n |d(x^{i+1}, x^i) + d(y^{i+1}, y^i)|, \quad (1)$$

where (x, y) is the coordinate of interactive learning information, d is the optimization coefficient, and i is the optimization times. The grouping sample regression analysis method [19] is used to mine the association rules of English

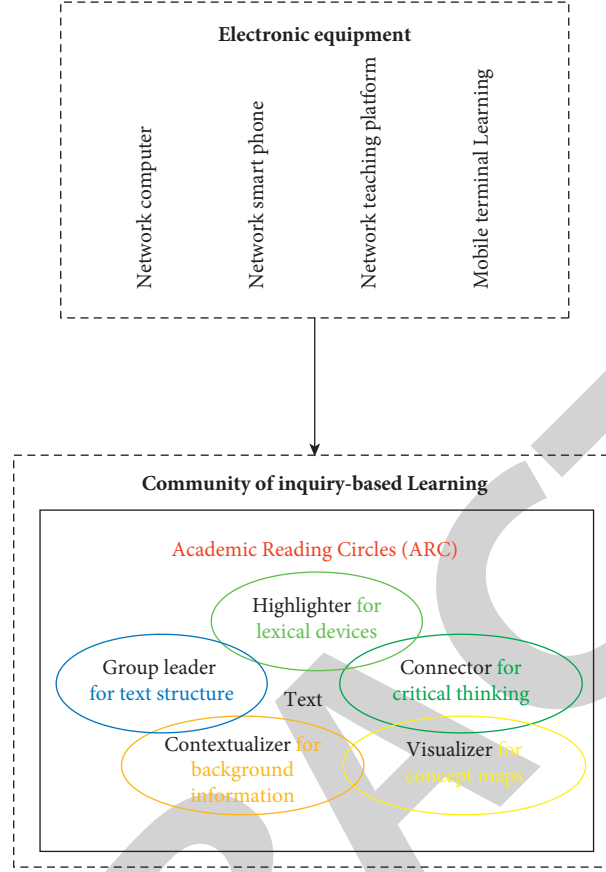


FIGURE 3: Creation of the community of inquiry-based learning.

mobile learning in the hybrid distributed terminal. Through statistical analysis and fusion decision, the fitness function of English mobile learning information in the hybrid distributed terminal is obtained:

$$X_{(i+1)} = a \pm \frac{p \cdot |p \text{ best} - D(x, y)|}{\ln u}, \quad (2)$$

where a and u are the weight vectors between 0 and 1, representing the distribution of English mobile learning information resources in the hybrid distributed terminal, p is the fitness coefficient, and $p \text{ best}$ is the correlation coefficient of English mobile learning information fusion in the hybrid distributed terminal. Through the nonlinear test, the reconstruction model of English mobile learning information fusion in the hybrid distributed terminal is obtained. Taking Q as the random distribution vector, the feature update vector Q' is obtained, and the comprehensive decision-making of English mobile learning information resource management in the hybrid distributed terminal is carried out. It is obtained that the fitness value of English mobile learning information scheduling in the hybrid distributed terminal is $V_k = (v_x^k, v_y^k)$, and the fuzzy estimation parameters of English mobile learning information scheduling in the hybrid distributed terminal are x' and y' . The number of English mobile learning information scheduling is k . Through rule set fusion, the sample regression analysis results are obtained:

$$\begin{cases} v_x^k t = x - kx' X_{(i+1)}, \\ v_y^k t = y - ky' X_{(i+1)}, \end{cases} \quad (3)$$

where t is the fusion time. Using the comprehensive sorting method, the English mobile learning information scheduling and spatial parameter sorting in the hybrid distributed terminal are carried out, and the mining function is obtained, which is obtained as follows:

$$C = \max \left\{ \sum_{i=1} [STA(i) + STA(i)] \right\} \left(\begin{matrix} v_x^k t \\ v_y^k t \end{matrix} \right), \quad (4)$$

where $STA(i)$ represents the convergence learning function and $ETA(i)$ represents the adaptive control function. According to the above analysis, in the ZigBee network environment, English mobile learning information sharing and fusion scheduling will improve the hybrid distributed terminal English mobile learning resources sharing and scheduling capacity [20].

2.4.2. Learning Information Sharing and Integration. The standard quantitative analysis of English mobile learning in the hybrid distributed terminal is carried out by subspace clustering analysis. Through comprehensive scoring decision, the edge function of fuzzy degree is obtained. Through the establishment of English mobile learning information

sharing model [21, 22] in the hybrid distributed terminal, combined with the large data mining method, the maximum distribution of spatial parameters is obtained as follows:

$$\begin{cases} \max \sum_{i=1}^n \frac{f(e(i))}{C(e, i)}, \\ 0 > f(e, i) > C(e, i), \end{cases} \quad (5)$$

where $f(\cdot)$ is the ambiguity edge function. Based on the methods of collaborative recommendation and semantic correlation fusion, the Semantic Detection Model of English mobile learning in the hybrid distributed terminal is established [23]. Through the method of comprehensive game, the standard quantitative function of English mobile learning in the hybrid distributed terminal is established, which is expressed as follows:

$$K = w_n + \frac{q_n}{f(e, i) - q_n}, \quad (6)$$

where w_n is the standard quantization coefficient and q_n is the standard quantization eigenvalue. Using the method of quantization analysis and roughness evaluation, the rough set eigenvalue of English mobile learning information distribution in the hybrid distributed terminal is obtained, and the optimal eigenvalue of English mobile learning information scheduling in the hybrid distributed terminal is obtained by constructing semantic ontology feature.

$$m_i = K \sum_{i=1}^n |d(x^{i+1}, x^i) + d(y^{i+1}, y^i)|. \quad (7)$$

According to the result of feature solution, the information scheduling and feature fusion of English mobile learning in the hybrid distributed terminal are carried out, and the information sharing mode is designed according to the result of resource scheduling.

2.4.3. Learning Information Resource Scheduling. Shared scheduling of English mobile learning information and fuzzy degree detection are carried out by means of fuzzy degree test and adaptive optimization [24, 25]. The information entropy of English mobile learning information resource is extracted, and the prior probability density function of English mobile learning information configuration is obtained as follows:

$$A = \sum_{x \neq 0, y \neq 0}^n \frac{\alpha(g, h)^x}{y}. \quad (8)$$

Here, $\alpha(g, h)$ represents the state function of the standard quantified distributed state set at scheduling node (g, h) for the optimal allocation of English mobile learning information under a hybrid distributed terminal, and its calculation formula is as follows:

$$\alpha(g, h) = \frac{1 - C_{n-h}}{C_g}, \quad n - h > g, \quad g > h. \quad (9)$$

For the integrated scheduling set of English mobile learning in a hybrid distributed terminal, the spatial distribution function of network information resources is N_f , and if $N_f/N = \delta$, the satisfaction level of English mobile learning information management in the hybrid distributed terminal is as follows:

$$U = A \times \log_2 \left(\partial \times \frac{R_{C_h}}{n_{C_h}} \right), \quad (10)$$

where n_{C_h} represents the degree of freedom function of the distributed node set of English mobile learning information in a hybrid distributed terminal. R_{C_h} represents the information fusion function. Therefore, the formula represents the information entropy of English mobile learning in a hybrid distributed terminal and estimates the parameters and resources through the weighted average method of information entropy [26].

Through the learning tracking algorithm, the convergence learning and adaptive control of English mobile learning information sharing in a hybrid distributed terminal are realized.

$$C(n) = \min \left\{ \sum_{i=1}^n \{ \text{STA}(i) + \max[\text{ETA}_1](i), \text{ETA}_2(i) \} \right\}. \quad (11)$$

In the learning information sharing mode, a data warehouse of English mobile learning information in a hybrid distributed terminal is constructed by means of management decision-making and integrated scheduling.

$$X_j(t+1) = X_{(i+1)} \pm \frac{\beta * |m \text{ best}(t+1) - X_j(t)|}{\ln[u_j(t)]}, \quad (12)$$

where $X_j(t)$ is the configuration function of English mobile learning information under the t -th generation hybrid distributed terminal. In the iteration, through state optimization, it is obtained that the fuzzy decision parameter of English mobile learning in the hybrid distributed terminal is β . Through the sharing and scheduling of learning information, the associated feature distribution set B is defined as follows:

$$B = \frac{\arg \max \{ \beta(X_j(t)) \mid j = 1, 2, \dots, n \}}{p \text{ best}}. \quad (13)$$

The resource allocation of English mobile learning information sharing in the hybrid distributed terminal is completed, and the optimized adaptive control function is obtained as follows:

$$F(X_j(t)) = N_f \sum_{j=1}^n A(X_j(t-1)). \quad (14)$$

2.5. User Interface Management Function Design. The hardware performance, software performance, and network performance of mobile devices are quite different, and the

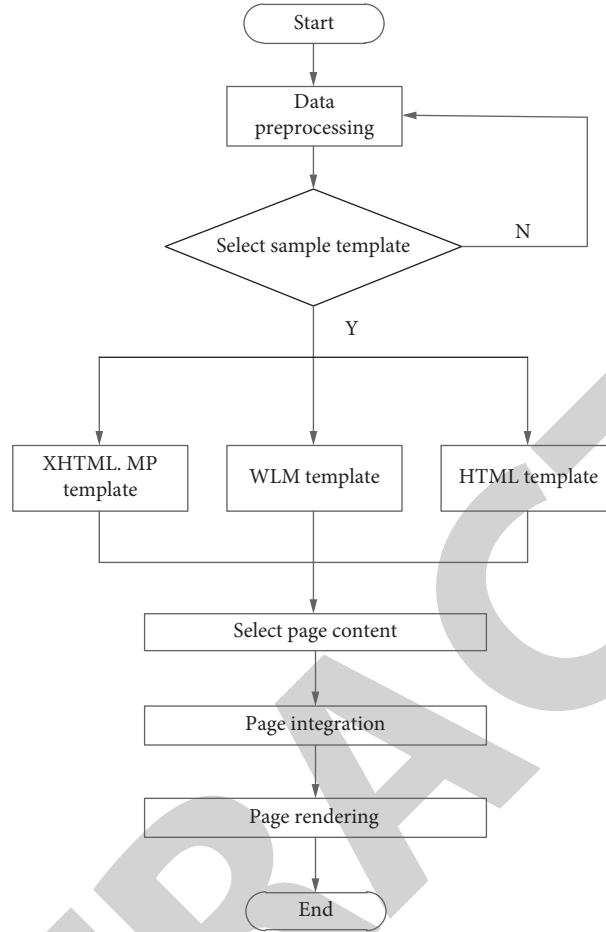


FIGURE 4: Content adaptive flow chart of mobile devices.

forms of learning resources are also diverse. The user interface management function provides user interface for different users and devices, which makes the teaching service provided by the mode widely applicable. User interface management function is realized by interface generation technology and learning resource reengineering technology. Interface generation technology selects page templates suitable for user devices according to the characteristics of user devices, and learning resource reorganization technology selects page contents suitable for user devices according to the characteristics of user devices and user browsing preferences, and fills the selected page contents into the corresponding page templates [27, 28]. The mobile device content adaptation process is shown in Figure 4. First, the device description file stored in the user's device is read, then the page template is selected according to the device characteristics described in the device description file, and the page content is selected according to device characteristics and user browsing preferences. Finally, the integrated page is presented to the user.

The user interface management function feeds the same teaching information and teaching activities back to the corresponding mobile devices with different user interfaces according to the characteristics of the mobile devices of the users, ensures the consistency of the browsing content of

different mobile devices, and reorganizes the teaching resources according to the resource quality and data volume of the browsing preferences of the users, so as to provide different teaching resources with the same content but different resource quality and data volume for the users with different browsing preferences and to adapt to the data transmission and processing capacity of the mobile devices [29].

3. Experimental Verification

The sample length of English online learning information sampling under the hybrid distributed terminal is 400. The MATLAB program is loaded for teaching resource information sharing, and the 8-channel synchronous sampling method is used for interactive learning information sharing. The sampling rate is $f_0 = 1$ KHz, the mutual information fusion management coefficient is $\sigma_0 = 0.2$, and the fusion degree coefficient of cross compilation is $\beta = 0.5$. The single terminal learning mode is used as the experimental control group, which is compared with the learning mode constructed in this paper.

3.1. Convergence Comparison. Based on the statistical distribution of English mobile learning information in Figure 5, this paper analyzes the characteristic quantity of English

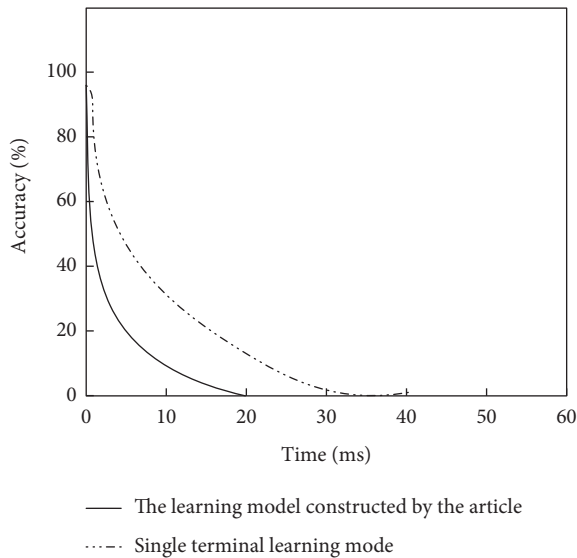


FIGURE 5: Convergence curve of English mobile learning information scheduling in the mixed distributed terminal.

mobile learning information in the hybrid distributed terminal, builds the model of English mobile learning information sharing in the hybrid distributed terminal, and extracts the feature of English mobile learning information by the statistical average analysis method. The result of convergence curve of English mobile learning information sharing in the hybrid distributed terminal is demonstrated in Figure 5.

According to the analysis of Figure 5, when the initial convergence error is the same, the method in this paper is completed in 20 ms to minimize the convergence error. The convergence error of single terminal learning mode reaches the lowest value at 40 ms. The above experimental data show that the proposed method has good convergence in English mobile learning information scheduling in the hybrid distributed terminal.

3.2. Accuracy of Learning Resource Allocation. The single terminal learning mode and hybrid distributed terminal mode are adopted to configure English learning resources, respectively, and the accuracy of their configuration is tested. The comparison results are shown in Table 2.

By analyzing Table 3, it can be seen that in the calculation process of multiple iterations, the average accuracy of the method in this paper reaches 0.9824, and the average accuracy of a single terminal is lower than that of the method in this paper. Therefore, it is apparent that the accuracy of English learning resource allocation in the hybrid distributed terminal is high.

3.3. Accuracy Analysis of Data Mining. Like a single terminal, this method requires background analysis, export, display, and issuing instructions to generate basic data such as effects and preferences of learning records, and there is no difference in programming. At the same time, it is necessary to manually conduct secondary data mining and write

programs according to the needs of teachers and students. Therefore, test the secondary data mining accuracy of the two methods, and the results are shown in Figure 6.

As can be seen from Figure 6, the accuracy of the method in this paper is higher than that of the single terminal learning mode. Because there is no convergence condition of adding interval constraint, it cannot guarantee whether the final data value obtained by the model conforms to the real value, and the data authenticity is high. This method uses the preference cost matrix to fill the bias formed by class preference, which improves the accuracy of preference sensitive learning and the accuracy of data mining.

3.4. Degree of Change in Student Attendance. Taking the student attendance rate in the actual quantitative direction in the above empirical plan as the assessment goal, the student attendance rate can obviously reflect students' acceptance of blended teaching with hybrid distributed terminals. Taking students of one class in grade 2 of a university as the assessment objective, record and observe the attendance record background data of all students signing in for this blended course. Their previous attendance in the single terminal is also recorded. The specific change rate of attendance is shown in Figure 7.

As can be seen from Figure 7, the real-time attendance rate of students in the same class in the blended mode is significantly higher than that in the previous single terminal learning mode, and their attendance rate curve has been in a stable and smooth trend with only very small fluctuation. This is because teachers use the online platform to sign in the classroom, and there will be no missed signing or signing on behalf of others. This will ensure the attendance of students to a great extent. Secondly, students can be engaged in the blended teaching mode. Teachers use the online platform to upload micro lectures and videos, and carry out some interesting and diversified activities, which cannot only consolidate knowledge but also attract students, stimulate interest, improve students' initiative and enthusiasm, and make students more willing to actively participate in relevant English courses.

3.5. Degree of Change in Students' Classroom Performance. Students' performance in class is one of the most important indicators of teaching and management. The main performance for the students in class speech or problem-solving, including learning attitude, learning progress, individual performance, and interaction between the teachers and students, a variety of factors, to determine the benchmark in these aspects, and through the comparative analysis, the same groups of students in two different teaching modes fulfilling the same task of ARC with texts of similar lexical ranges and styles, the results are shown in Table 3.

It can be seen from Table 3 that the performance of students in the class speech link under the blended teaching mode classroom is very prominent, with an average of 95.6 times, indicating that almost all students in the class actively participate in the activity.

TABLE 2: Comparison of accuracy of learning resource allocation.

Number of iterations	Paper method	Single terminal learning model
10	0.981	0.824
20	0.982	0.811
30	0.981	0.872
40	0.984	0.882
50	0.984	0.890
60	0.986	0.817
70	0.985	0.813
80	0.989	0.799
90	0.978	0.817
100	0.979	0.833
Average value	0.988	0.8466

TABLE 3: Comparison of classroom performance changes.

	Lectures/times		Teacher student interaction/time		Learning progress (%)	
	Hybrid terminal	Single terminal	Hybrid terminal	Single terminal	Hybrid terminal	Single terminal
1. Group	7	6	6	3	97.2	80.5
2. Groups	6	4	5	3	98.3	82.2
3. Groups	6	3	5	4	90.9	80.4
4. Groups	6	5	4	6	91.3	90.3
5. Groups	7	5	6	5	92.1	84.2
6. Groups	6	4	5	5	90.9	86.2

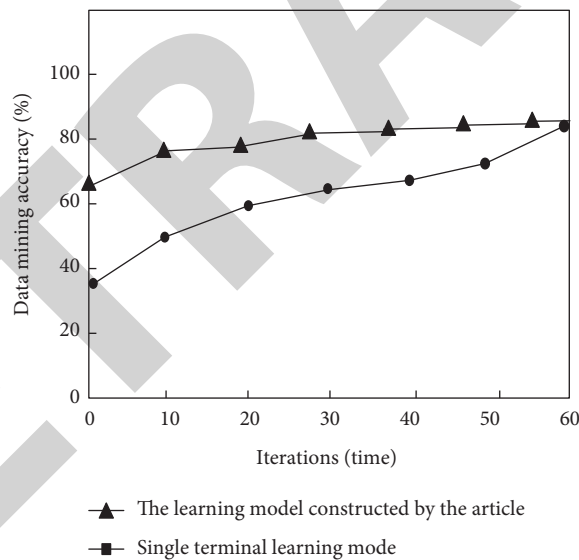


FIGURE 6: Comparison of data mining accuracy.

The interaction between teachers and students in the single terminal learning mode is very limited. In the traditional single terminal mode, the average number of interactions in each group is 4, which also indicates that for most students, the class is not interesting, the platform is not friendly or convenient to access, and some activities or quizzes cannot appropriately activate classroom atmosphere and arouse students' interest. Active and deep thinking is also vital for EFL classes. However, the classroom interaction under the single terminal learning mode is more rigid and monotonous and at a low frequency, thus ignoring students' interest and diversified personalities, without giving students

room to perform both individually and collaboratively. Moreover, it is hard for students in the single terminal learning mode to create a learning community to carry out collaborative study.

The blended teaching mode with the hybrid distributed terminal in this paper fully considers students' interest and learning styles, featuring novel teaching methods, class design, and types of interaction. There are also some supplementary short videos and interaction links on the online platform to arouse students' interest, activate class, enhance learning atmosphere, and increase effective interaction. Furthermore, the creation of the community for inquiry-

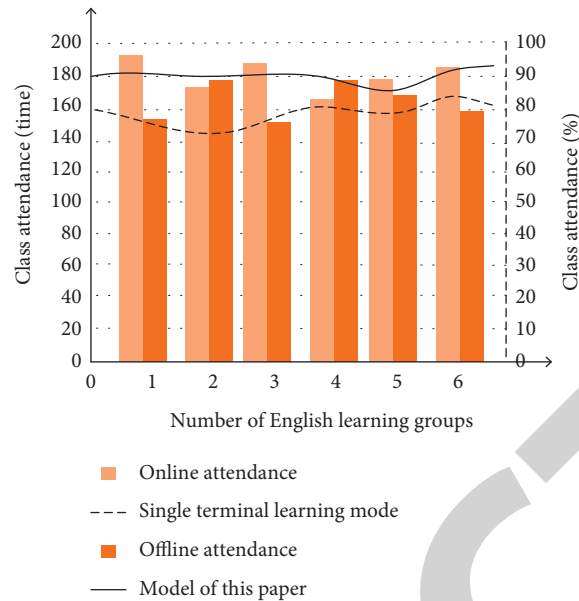


FIGURE 7: Comparison of attendance changes.

based learning will dramatically enhance students' performance both individually and collaboratively, facilitate deep learning, and increase memory retention rates, which will also ease burden for students at low English levels with the scaffolding of students at high levels. In addition, some standardized quizzes have been set up for some introverted students to appropriately participate in classes and interact with teachers and peers to improve the learning environment, so that more students can be adjusted to this learning mode, enhance enthusiasm, and enable all to achieve progress.

4. Conclusion

This research explores a mobile learning model for EFL courses constructed in the hybrid distributed terminal. Select an appropriate platform which helps build a community of inquiry-based learning in the blended learning mode and to optimize mobile learning software for the hybrid distributed terminal. By mining and scheduling learning resources and the effective design of the user interface management function, the experimental results show that the mobile learning model in the hybrid distributed terminal in this study has good convergence and feasibility, higher accuracy of learning resource allocation, and data mining. In the designed learning mode, EFL learners might obtain the desired effect for English acquisition.

Data Availability

The raw data supporting the conclusions of this article will be made available by the corresponding author, without undue reservation.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

Acknowledgments

This work was sponsored in part by University-Industry Collaborative Education Program (202101266022 and 202102420004), Shandong University Education Reform Program (2021Y279), and Shandong University "Hidden Curriculum" Program (2021S03).

References

- [1] T. Xue, "Chemistry course network teaching based on key information search and big data cloud platform," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 3, pp. 1–12, 2020.
- [2] B. Zhao, "The construction of college English intelligent teaching mode guided by POA theory in the new mobile media environment," *Theory and Practice of Education*, vol. 39, no. 03, pp. 53–54, 2019.
- [3] Y. Meng and J. L. Chen, "On dynamic evolution of foreign language learning modes at information age: a scientometric analysis in CiteSpace," *Foreign Language Teaching*, vol. 168, no. 04, pp. 36–42, 2019.
- [4] D. M. Olivé, Q. H. Du, M. Reynolds, M. Dougiamas, and D. Wiese, "A quest for a one-size-fits-all neural network: early prediction of students at risk in online courses," *IEEE Transactions on Learning Technologies*, vol. 12, no. 2, pp. 171–183, 2019.
- [5] N. Bagger, S. Kristiansen, M. Sorensen, and T. Stidsen, "Flow formulations for curriculum-based course timetabling," *Annals of Operations Research*, vol. 280, no. 1–2, pp. 121–150, 2019.
- [6] P. Guo, "MOOC and SPOC, which one is better?" *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 13, no. 8, pp. 5961–5967, 2017.
- [7] K. Forinash and B. Whitten, "Resource letter TEP-1: resources for teaching environmental physics," *American Journal of Physics*, vol. 87, no. 6, pp. 421–432, 2019.
- [8] M. G. Moore, G. Kerarley, and S. D. Wadsworth, "Distance education: a system view," *Open Learning*, vol. 8, no. 3, pp. 3–12, 1996.

- [9] M. G. Moore, "Editorial: three types of interaction," *American Journal of Distance*, vol. 3, no. 2, pp. 1–7, 1989.
- [10] E. L. Bengtsson, F. Rusek, P. C. Karlsson, F. Tufvesson, and O. Edfors, "Simulation of multiple-antenna terminal performance in massive MIMO systems based on indoor measurements," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 418–427, 2020.
- [11] C. J. Bonk and C. R. Graham, *Handbook of Blended Learning: Global Perspectives, Local Designs*, Pfeiffer Publishing, San Francisco, CA, USA, 2006.
- [12] T. Seburn, *Academic Reading Circles*, Create Space Independent Publishing Platform, Scotts Valley, California, USA, 2016.
- [13] E. Dale, "The cone of experience," in *Classic Writings on Instructional Technology*, D. P. Ely and T. Plomp, Eds., Dryden Press, New York, NY, USA, 1946.
- [14] J. Rhem, "Deep/surface approaches to learning: an introduction," *National Teaching and Learning Forum*, vol. 5, no. 1, pp. 1–5, 1995.
- [15] W. Houghton, *Engineering Subject Centre Guide: Learning and Teaching Theory for Engineering Academics*, HEA Engineering Subject Centre, Loughborough, UK, 2004.
- [16] R. J. Fendler, C. Ruff, and M. M. Shrikhande, "No significant difference – unless you are a jumper," *Online Learning*, vol. 22, no. 1, pp. 39–60, 2018.
- [17] D. A. Wood, "Net ecosystem carbon exchange prediction and insightful data mining with an optimized data-matching algorithm," *Ecological Indicators*, vol. 124, no. 82, Article ID 107426, 2021.
- [18] D. Praveen Kumar, T. Amgoth, and C. S. R. Annavarapu, "Machine learning algorithms for wireless sensor networks: a survey," *Information Fusion*, vol. 49, pp. 1–25, 2019.
- [19] V. V. Chistyakov, S. Kazakov, M. Grevtsev, and S. Solov'yov, "Nonlinear-regression based algorithm of chemical sensor's signal processing for selective de-tecting of various species in artificial air," *Technical Physics Letters*, vol. 2021, no. 6, p. 15, 2021.
- [20] C. Shao, H. Park, H. Roh, W. Lee, and H. Kim, "PolarScout: Wi-fi interference-resilient ZigBee communication via shell-shaping," *IEEE/ACM Transactions on Networking*, vol. 28, no. 4, pp. 1587–1600, 2020.
- [21] R. Leszczyna, T. Wallis, and M. R. Wrobel, "Developing novel solutions to realise the European energy - information sharing & analysis centre," *Decision Support Systems*, vol. 122, pp. 113067.1–113067.11, 2019.
- [22] N. Y. Ermolova and O. Tirkkonen, "SIR statistics and average rates in cooperative spectrum-sharing networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 8178–8182, 2019.
- [23] A. Braoveanu and R. Andonie, "Integrating machine learning techniques in semantic fake news detection," *Neural Processing Letters*, vol. 53, no. 2, pp. 1–18, 2020.
- [24] S. Aalto, P. Lassila, and I. Taboada, "Whittle index approach to opportunistic scheduling with partial channel information," *Performance Evaluation*, vol. 136, pp. 102052.1–102052.23, 2019.
- [25] S. Radhika and P. Rangarajan, "Fuzzy based sleep scheduling algorithm with machine learning techniques to enhance energy efficiency in wireless sensor networks," *Wireless Personal Communications*, vol. 118, no. 4, pp. 1–20, 2021.
- [26] C. Morariu, O. Morariu, S. Răileanu, and T. Borangiu, "Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems," *Computers in Industry*, vol. 120, Article ID 103244, 2020.
- [27] S. F. J. Rodríguez, M. A. Conde, P. Ponsa, and L. M. Muñoz, "Design and evaluation of a graphical user interface for facilitating expert knowledge transfer: a teleoperation case study," *Universal Access in the Information Society*, vol. 18, no. 2, pp. 1267–1278, 2019.
- [28] R. Zhu, C. Ye, L. Fan, and W. Chen, "Design of medical equipment system based on neural network algorithm and network feature," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 1–11, 2020.
- [29] V. Subramaniaswamy, R. Logesh, D. Malathi, V. Vijayakumar, H. R. Karimi, and M. Karuppiah, "Effective user preference mining-based personalised movie recommendation system," *International Journal of Computer Aided Engineering and Technology*, vol. 13, no. 3, 371 pages, 2020.