Evaluation of Mobile Learning Ability of English Teaching Based on AHP

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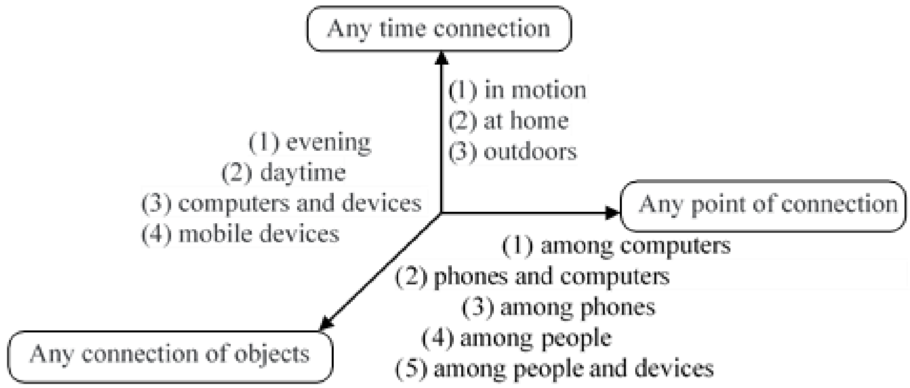
In order to improve the mobile learning ability of English teaching, this paper optimizes the connection among the various layers of the evaluation index system of mobile learning ability of students based on Internet of things and analytic hierarchy comprehensive evaluation method, and greatly reduces the uncertain factors in the evaluation process to a large extent. After calculating the weight matrix and membership matrix of each layer index, this paper establishes the econometric model of comprehensive evaluation results. The final purpose is to make use of multi-level comprehensive evaluation method, solve the subjective factors that affect mobile learning ability effectively bring bigger error for accurate evaluation of English teaching in the development of mobile learning ability, which has great reliability and practicability.

Keywords: internet of things, English teaching, mobile learning, analytic hierarchy process (AHP)

INTRODUCTION

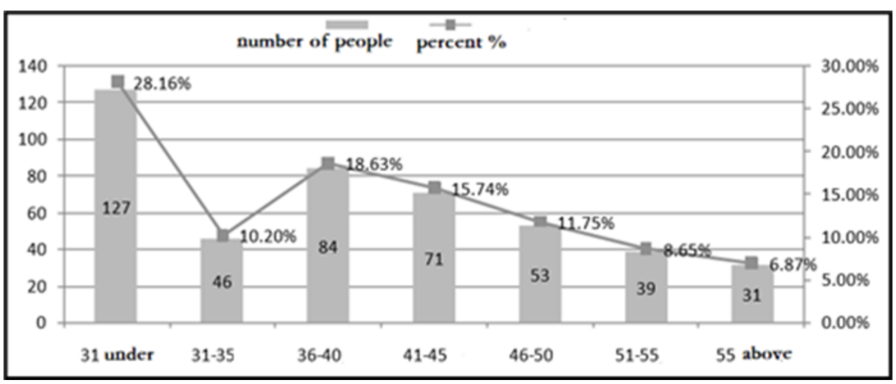
Against the backdrop of the COVID-19 pandemic, the internet has become the most important means of interpersonal. Especially in English teaching (Dashtestani, 2016), how to make use of the link dimension in the Internet of Things (as shown in Figure 1) to effectively carry out remote network teaching, and it digitizes and networked everything, and it realizes efficient information interaction between objects, objects and people, and people and the real environment, and it integrates all kinds of information technology into social behavior through new service modes (Traxler, 2017), which is a higher realm achieved by comprehensive application of information technology in human society. Internet of Things has expanded the development space of internet applications and promoted the development of emerging industries such as intelligent information services. It is playing an important role in the development and application of intelligent education, especially in the field of English teaching and educational means innovation (Byun et al., 2014).

FIGURE 1
LINK DIMENSIONS IN IOT



According to relevant statistics, China had 910 million 4G users and 140 million new users by the end of 2017. In addition, China is now in a leading position in 5G technology. China has fully entered the 5G era. With the help of Internet of Things technology platform, more and more people begin to get used to using "mobile devices" for "mobile learning" (as shown in Figure 2). Therefore, "mobile learning" has developed from a technical device to an English teaching (Mellati and Khademi, 2015). With the rapid development and large number of mobile users, the development of functional platforms and systems emerge in an endless stream such as personalized, intelligent and data. From "mobile technology" to "mobile devices" to "mobile applications" and finally to "mobile learning", "mobile" has evolved from a state of technical devices to a feature of a new way of learning (Shih et al., 2010).

FIGURE 2
POPULATION AGE DISTRIBUTION OF MOBILE LEARNING



As technology like Internet of Things continues to revolutionize learning, the continuous development of technology has promoted the reform of learning, which has changed the learning time, space, content, mode and interactive mode. The traditional face-to-face education mode is far from keeping up with the growth rate of knowledge, so mobile learning has gradually come into the public eye (Yang, 2005). Mobile learning is not limited by time and space, and in the learning process, communication and interaction between teachers and students and among different students can still be carried out with the help of Internet of Things (Impedovo, 2011). At the same time, with the increase of learning tools, learners' grasp of the characteristics of learning tools and flexible choice and application of learning tools show an increasingly strong driving force, which is manifested as the essential characteristics of learning force from a technological perspective (Chen, 2010). Mobile learning plays a huge role in different stages of learning. It does not only affect the transfer of knowledge, but also intangibly develops learners' learning power and gives birth to new forms of learning power under mobile learning tools (Gu, 2012).

Mobile learning is not only produced in the fast-paced era, but also will continue to develop in this era. It is a necessary process for mobile technology to change from assisted learning to integrated learning and then to the development of mature mobile learning mode. Learners want to completely conquer mobile learning and use mobile learning mode to better promote the acquisition of knowledge and life growth. Therefore, it is necessary to have the learning ability adapted to mobile learning (Park et al., 2012). At present, the overall development of mobile learning of learners is not fast, and the development of all dimensions is not balanced. Among the elements of mobile learning ability, in addition to the influence of learners themselves, the environment they are in and the organizational model of learners, the key elements of the development of mobile learning ability of college students are also reflected in the selection of learning time and learning style (Dhawan, 2020).

REVIEW OF THE LITERATURE

Some foreign scholars have investigated the factors influencing the willingness to use online learning by taking students in developing countries as the survey objects. The results show that psychological preparation and skills affect perceived usefulness and perceived ease of use, and thus indirectly affect willingness to use online learning (Singh and Thurman, 2019; Mayer, 2019; Wei and Chou, 2020; Dumford and Miller, 2020). Some domestic scholars have investigated the factors influencing students' adoption of online Learning English. The results show that effort expectation, performance expectation, social influence and convenience all affect students' behavioral intention of online learning (Zheng et al., 2020; Tsai et al., 2018; Ariffin et al., 2021). The research process of these scholars generally adopts qualitative research methods and lacks quantitative research results. At the same time, the accuracy of some research results is affected because there is no microscopic research process, such as English learning (Putri and Sari, 2021; Liang and Pang, 2021).

This paper focuses on exploring how learners can make good use of Internet of Things technology tools to carry out learning, and learners' learning ability can be used as the measurement standard and index of learning. With the rapid development of online English teaching, various training institutions share their own resources through the Internet platform. English learners have also increased their knowledge and ability through online learning, but the abnormal development of the market makes the competition become extremely fierce, and the effect of online English learning has not been well improved (Cakrawati, 2017). Online English teaching, from scratch to scratch, from weak to strong, from offline operation to online + offline double combination, let the whole people realize the importance of English. At present, the popularity of the Internet and internet-connected devices, in the past three years, PC, IPAD and smart phones and other devices have rapidly become popular in homes and schools, solving the hardware problem of online education (Guo et al., 2008).

METHODOLOGY

(AHP) Analytic Hierarchy Process

Analytic hierarchy Process (AHP) can optimize the connection among each layer and its sub-fuzzy model, and greatly reduce the uncertain factors in the evaluation process (Kumar and Kumar, 2019). Therefore, this paper uses AHP as the research basis of fuzzy comprehensive evaluation. The basic steps of the AHP:

Step1: To determine the index system of AHP according to the comprehensive analysis, and determine the evaluation factors of the target layer (An), criterion layer (Bn) and index layer (Xij).

Step2: In the index system, the indexes at the same level are compared pair-by-pair by their own experience or organizational experts, and the judgment matrix is constructed: $X=(x_{ij})_{n\times n}$, whose elements are as follows:

$$x_{ij} > 0, x_{ij} = \frac{1}{x_{ji}}, \sum_{i}^{n} x_i = 1, (i, j = 1, 2, \ldots, n) \quad (1)$$

where, the ratio of importance of element i to element j is xij.

Step 3: To calculate the weights. For each row element of the judgment matrix, the product Di of each row element is calculated with the behavior vector, and the calculation formula is shown as follows.

$$D_i = \prod_{i}^{n} y_i, (i = 1, 2, \ldots, n) \quad (2)$$

For the n-order judgment matrix, the result of mi is calculated according to the above equation, and the normalized eigenvector value of each row of the judgment matrix is calculated, and the eigenvector W=(w1, w2,…,wn)T. The calculation formula is as follows:

$$w_i = \frac{\sqrt[n]{D_i}}{\sum_{i=1}^{n} \sqrt[n]{D_i}} \quad (3)$$

According to the n-order judgment matrix X and the corresponding eigenvector W, calculate the largest eigenvalue λmax of the judgment matrix X.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{Xw_i}{nw_i} \quad (4)$$

Step 4: Total hierarchy ordering and consistency checking. Because of the complexity of objective things and the fuzziness and diversity of people's understanding of things, the given judgment matrix may not be completely consistent, so it is necessary to carry out a consistency test. When the order of the judgment matrix is less than or equal to 2, there is no possibility of the above inconsistency, then it can be directly judged that it satisfies the condition of complete consistency. If the order is greater than 2, you need to perform consistency judgment. The consistency index CI value of the judgment matrix of each layer can be expressed as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (5)$$

After calculating the relative importance of factors at all levels, the overall weight of factors at all levels on the overall evaluation target can be calculated according to the principle from high to low levels, so the total ranking of levels is needed. Then the random consistency ratio of the next layer is:

$$CR = \frac{CI \sum_{j}^{n} x_j}{RIx_j} \quad (6)$$

where, RI is a randomness indicator.

Multi-Level Comprehensive Evaluation Method

The multi-level comprehensive evaluation method uses the comprehensive evaluation method to effectively solve the large error caused by subjective factors based on the AHP, which has great reliability and practicability (Wang and Xu, 2021). When the problem has uncertainty and fuzziness, the comprehensive evaluation model can be used to deal with it (Meng, 2020). After considering all kinds of influencing factors comprehensively, this paper chooses multi-level comprehensive evaluation method based on AHP. As for the analysis of the weight of multiple evaluation indicators, most studies are given on the basis of mastered experience, which is highly subjective (Kanekar and Sharma, 2009). In this paper, AHP is selected to construct the index system and determine the weight of each evaluation index.

(1) Membership matrix. According to the problem evaluation index determined by the above AHP, two finite sets are assumed according to the comprehensive evaluation method: E={e1, e2,…,en}, set V={v1,v2,…,vn}. E represents the set composed of evaluation factors, and V represents the set of evaluation grades. After considering all kinds of influencing factors, the best evaluation result is obtained from the alternative concentration. To a certain extent, these evaluation indicators are all fuzzy and uncertain, and some of them can be regarded as definite values. And the membership function must consider the change law of each single index. When there are many indexes, the indexes must be classified, and the membership degree R of each evaluation grade can be calculated according to the actual value of each evaluation index, which can be expressed as follows:

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{7}$$

where, rij represents the membership degree of ei evaluation to grade vi, and after normalization, ∑ rij =1. According to the range ki divided by the evaluation grade, the calculation of the positive effect index Svi. According to the range ki divided by comparison and evaluation grade, the calculation formula of negative effect index Svi.

(2) Comprehensive evaluation result model. According to the weight matrix and membership matrix obtained above, this paper establishes an econometric model for the comprehensive evaluation result Y:

$$Y = XR = \left(x_1, x_2, \ldots, x_m\right) \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} = \left(y_1, y_2, \ldots, y_m\right) \tag{8}$$

where, yi represents the comprehensive membership degree of evaluation index to evaluation grade vi. In this paper, the calculation model of yi is chosen as follows:

$$y_i = \min\left\{1, \sum_i^n \min\left(x_i, r_{ij}\right)\right\}, i = 1, 2, \ldots, n \tag{9}$$

For the evaluation and analysis of the comprehensive evaluation result Y, the maximum membership method and the comprehensive scoring value method are usually used. Among them, the maximum degree of membership method is to select the maximum degree of membership from each evaluation result vector in Y, and consider that the evaluation index belongs to this evaluation grade. The critical value of each evaluation grade can be calculated by comprehensive analysis. Then the paper uses the corresponding vector in Y to calculate the comprehensive score F.

$$F = \frac{\sum_i^n \left(y_i^t \times x_i\right)}{\sum_i^n y_i^t} \tag{10}$$

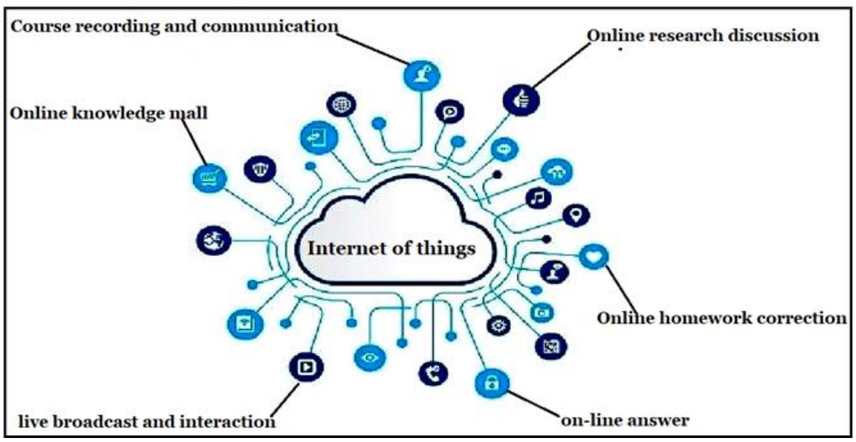
where, t is the reduction coefficient, the purpose of which is to weaken the weight position of the larger yi. When t tends to infinity, the comprehensive scoring method is essentially the maximum membership method.

RESULTS AND DISCUSSION

Building Evaluation Index System

The level of learners' mobile learning ability will affect their response to the unpredictable learning environment in the future. It is both natural and urgent to cultivate learners' mobile learning ability and solve problems in the development of learning ability (Hwang & Chang, 2011), as shown in Figure 3. Learners have found that the key elements of the development of mobile learning ability are also reflected in the selection of learning time and learning mode (Looi et al., 2020).

FIGURE 3
SOLUTION FOR ONLINE EDUCATION



(1) Average time spent online on mobile devices per day. The descriptive statistical analysis of the respondents' average daily online time on mobile devices is shown in Table 1. As can be seen from Table 1, the number of people who use mobile devices for more than 4 hours on average every day accounts for 11.40%, of which 25.70% spend fixed learning time, and 30.20% of them spend 3-4 hours surfing the internet on mobile devices on average every day, and 25.70% of them set their rest time as study time, and 47.80% of the people use mobile devices for 2-3 hours a day on average, and 8.10% of them spend learning time in traffic. 9.30% used mobile devices for 1-2 hours per day on average, among which 26.20% spent random learning time. On average, 1.30% of people spend less than one hour surfing the Internet on mobile devices every day, and 4.80% of them use fragmented time to study.

TABLE 1
CHOICE OF ONLINE TIME AND MOBILE LEARNING TIME

Online time	Proportion of people (%)	Mobile learning time point	Proportion of time (%)
More than 4 hours	11.40	fixed time	25.70
4—3 hours	30.20	break Time	35.20
3—2hours	47.80	bus time	8.10
2—1hours	9.30	random time	26.20
Less than 1 hour	1.30	piece of time	4.80

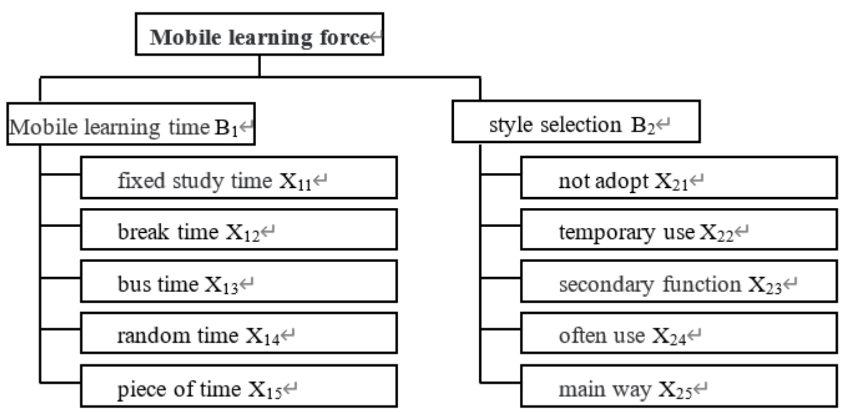
(2) Mobile learning-based learning mode. Table 2 shows the statistical analysis of the mobile learning-oriented learning methods of the respondents. It can be seen from Table 2 that most respondents believe that mobile learning will become the main way of learning in the future, and 38.6% of them hold this attitude. The number of people who think mobile learning is a regular way is also quite large, accounting for 30.20%. The number of people who think mobile learning has auxiliary function is relatively small, accounting for 20.10%. The number of people who think mobile learning only temporarily uses functions is even less, accounting for 10.30%. The number of people who think mobile learning is basically useless is the least, accounting for 0.80%. These data show that learners have a positive attitude towards mobile learning, and most of them believe that mobile learning has a great development space and will become the main way of learning in the future.

TABLE 2
STATISTICS OF LEARNING METHODS MAINLY BASED ON MOBILE LEARNING

Mobile Learning options	**proportion of people (%)**
not adopt	0.80
temporary use	10.30
secondary function	20.10
often use	30.20
main way	38.60

This study is to explores the composition of the evaluation index system for college students to take mobile learning as the main learning mode based on the analytic hierarchy Process (AHP), as shown in Figure 4.

FIGURE 4
EVALUATION INDEX SYSTEM



Judgment Matrix

In the analytic hierarchy process (AHP), according to the relative importance of each level index, this paper constructs the numerical judgment matrix by quantifying the evaluation factors. In order to clarify the evaluation index of mobile learning ability of college students in intelligent higher education system [29], the score of each evaluation factor was determined by expert scoring method, and the quantitative judgment matrix was obtained, as shown in Table 3-5.

TABLE 3
JUDGMENT MATRIX A1(A-B)

A	B_1	B_2
B_1	1.00	5.00
B_2	0.20	5.00

TABLE 4
JUDGMENT MATRIX A2(B1-X)

B_1	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
X_{11}	1.00	0.50	1.00	0.33	0.20
X_{12}	2.00	1.00	2.00	0.50	0.25
X_{13}	1.00	0.50	1.00	0.33	0.20
X_{14}	3.00	2.00	3.00	1.00	0.33
X_{15}	5.00	4.00	5.00	3.00	1.00

TABLE 5
JUDGMENT MATRIX A3(B2-X)

B_2	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}
X_{21}	1.00	1.00	0.33	0.33	0.33
X_{22}	1.00	1.00	0.33	0.33	0.33
X_{23}	3.00	3.00	1.00	1.00	1.00
X_{24}	3.00	3.00	1.00	1.00	1.00
X_{25}	3.00	3.00	1.00	1.00	1.00

Check Consistency

According to the judgment matrix, this paper carries on the consistency test respectively. If the consistency condition is met, the hierarchical order is performed. If the consistency condition is not met, it will be modified under the principle of not violating the law of expert evaluation and scoring until the judgment matrix meets the consistency condition. In this paper, with the help of Matlab and other software, the indicators are as follows:

TABLE 6
RESULT OF INDEX OF CORRELATION

Index	**A-B**	B_1**-X**	B_2**-X**
λ_{max}	2.00	7.10	8.00
$W=(w_1,w_2,\ldots,w_n)^T$	$(0.88,0.13)^T$	$(0.07,0.12,0.07,0.20,0.40)^T$	$(0.06,0.06,0.20,0.20,0.20)^T$
CI	0.00	0.01	0.00
RI	0.00	1.30	1.40
CR	--	0.01	0.00
check consistency	complete consistency	consistency	complete consistency

According to the above calculation results, this paper not only obtains the consistency test CI and RI values of criterion layer B, but also obtains the weight of target layer A. In this way, all indicators can be ordered in a total hierarchy, that is, the random consistency ratio of the next layer is:

$$CR = \frac{CI \sum_{j}^{n} x_j}{RIx_j} = (0.88 \times 0.01) / (0.88 \times 1.30 + 0.13 \times 1.40) = 0.006 < 0.1 \tag{11}$$

The critical value of each evaluation grade can be calculated by comprehensive analysis. Then take the comprehensive score was calculated by the corresponding vector in the Y value $F = \frac{\Sigma_i^n (y_i^t \times x_i)}{\Sigma_i^n y_i^t}$, which can get average score 0.40 for college students for mobile internet learning time a day. The score of college students choosing mobile internet learning is 0.65. According to the calculation principle of comprehensive score value, if F=0.20-0.30, it is considered that the corresponding score is seriously unbalanced. If F=0.30 -0.50, it is considered that the corresponding scoring grade is unbalanced. If F=0.50-0.70, the corresponding scoring grade is considered to be critical. If F>0.70, it is considered that the corresponding scoring grade is in equilibrium state, that is, the evaluation index is in a state of safe development.

CONCLUSIONS AND RECOMMENDATIONS

In the context of the COVID-19 pandemic, the technology of Internet of Things can unleash its potential benefits in smart education. According to the link dimension in Internet of things, this paper adopts the AHP comprehensive evaluation method to study and optimize the evaluation index system of online education on Internet of Things platform. According to the comprehensive evaluation method, the evaluation grade value is quantitatively studied. This paper finds that the overall development level of mobile learning ability of online learners is low, and the development of different dimensions is not balanced. Despite the positive development of learners' motivation for mobile learning, the development of mobile learning ability is insufficient, and the development of perseverance in choosing mobile learning is unbalanced. Among the elements of mobile learning ability, although learners have a good development in mobile resource collection ability, their self-motivation in mobile learning is relatively poor. At the same time, learners' mobile learning ability is also different in different ages, majors and places of origin, which interferes with the improvement and development of intelligent education system.

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