College English Flipped Classroom Teaching System Based on Smart Sensor Network

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ABSTRACT

This study aims at the autonomy dimension of students in the college English flipped classroom based on the help of a sensor network to investigate and explore the status quo in each stage of the college English flipped classroom, analyse the shortcomings, and propose teaching suggestions. The college English curriculum reform has been in effect for more than 10 years since it started in 2004. Under the foreshadowing of information-assisted teaching, the flipped classroom teaching model also influences the reform of the Chinese traditional teaching model. The research conducted a one-semester flipped classroom teaching of college English in the subjects’ classes. The study analyses the data using SPSS software for correlation analysis and finds that the correlation coefficient (r value) between the total score of autonomy and English performance is 0.904, the sig value is <0.05, and the two component values are highly correlated. Student autonomy is not only important in the English flipped classroom but also has a significant impact on students’ performance.

KEYWORDS

College English, Flipped Classroom, Smart Sensor, SPSS Software, Teaching System

1. INTRODUCTION

Traditional college English teaching pays attention to the process of pre-class preparation, in-class learning and after-class review, whilst student learning mainly occurs in the teaching process of classroom teachers. With the in-depth integration of modern information technology and foreign language teaching, students’ learning resources are more abundant, and their dependence on teachers is gradually reduced. Autonomous learning has gradually become an important way of foreign language learning, and Foreign language teaching is also changing from ‘teaching’ to ‘learning’ as the centre and from ‘teacher’ to ‘student’ as the centre.

Many experts at home and abroad also have their own opinions on the research of smart sensors and flipped classrooms (FCs). Thai, Wever and Valcke (2017) examined the comparison between the FC learning environment and blended learning (BL), traditional learning (TL) and e-learning (EL)
environments. They also compared the different performances of FC learning and self-learning. As a teacher, Sohrabi and Iraj (2016) taught students through the FC model for the first time. They found that students prefer resources other than lectures, such as technology, entertainment and design (TED) and documentaries, and watching English videos are challenges and opportunities for students. Jovanovic et al. (2017) examined tracking data to identify learning strategies in FCs. They found that the clustering of students reveals four learning strategies. Moreover, five student files are classified and recorded based on the clustering of strategies, and the results show that students tend to change less effective strategies (Jovanovic et al., 2017). Mcnally et al. (2017) believed that although FCs are popular, their effectiveness in achieving greater participation and learning outcomes currently lacks much empirical evidence. Asiksoy and Zdamli (2016) obtained experimental results through physical concept tests, motivation questionnaires, physical self-sufficiency scales and semi-structured interviews. They found that the scores of the experimental group students were higher than those of the control group, and the enthusiasm and self-sufficiency of the experimental group students also increased. Subsequently, they conducted semi-structured interviews with the students in the experimental group and found that they had a positive attitude towards the FC method. The student perception data of the Cotta KI test also show that most students prefer the flip method to the traditional one. This study shows that the FC method used to teach drug calculations can improve student performance and satisfaction (Cotta et al., 2016).

Previously, interacting and studying cooperatively directly in the classroom were very difficult for students. The reason is that students need to understand the knowledge to be used to complete these classroom tasks. However, in traditional teaching, where only the classroom is taught, such goals are difficult to achieve. Internet technology refers to an information technology developed on the basis of computer technology. Internet technology connects different devices through the wide area network of computer network, speeds up the transmission speed of information and broadens the access channel of information, promotes the development of various software applications, and changes people’s life and learning styles. With the development of network technology, computer terminals and online videos have become convenient and effective teaching tools. When they are combined with the face-to-face classroom learning environment, under the support of the constructivist theory, this perfect classroom teaching revolution occurs, and the FC is the product of this innovation (Garcia et al., 2017). Today’s student life is inseparable from Internet technology, and they connect with friends through the Internet. Therefore, this native tool is very feasible to use for reforming the teaching model.

The innovation of this paper is as follows: 1. The research used SPSS software to analyze the data. 2. Aiming at the autonomy dimension of students in the college English flipped classroom, it investigated and explored the current situation of each stage of the college English flipped classroom with the help of sensor networks, analyze the deficiencies and put forward teaching suggestions.

2. CLASSROOM MANAGEMENT SYSTEM BASED ON SMART SENSOR NETWORK

Sensor network is a computer network composed of many spatially distributed automatic devices that use sensors to monitor physical or environmental conditions (such as temperature, sound, vibration, pressure, motion or pollutants) at different locations cooperatively. The development of wireless sensor networks originated from military applications such as battlefield monitoring. Nowadays, wireless sensor networks are used in many civil fields, such as environmental and ecological monitoring, health monitoring, home automation, and traffic control.

The intelligent classroom management system is divided into the following six modules:

Server side: this module is the data transfer station of the entire system, responsible for the core data processing, data storage, data query and other functions. The Android terminal, teacher’s phone and camera will all send data to the server, and the server provides a receiving interface for all data. After the data are processed, they are stored in the corresponding table of the database (Dissanayake, Pasqual & Athapattu, 2017). These data provide the functions of adding, deleting, modifying and
checking all data and managing with administrator authority. In addition, using the crontab timer under Linux to convert the course time into the timer to start the task time, the timer task is set to control the camera to take pictures and store them. In this way, the camera automatically takes pictures of the students in class, and the server accurately cuts the taken pictures according to the specific location information of the classroom uploaded by the student app and obtains the class photos of themselves, which are stored on the server for secondary attendance (Naha, Wu & Velmathi, 2020).

Wireless router module: when a device is connected to the wireless network of the router, it obtains the detection request frame W actively sent by the device and analyses the MAC information according to the frame format. In addition, the router provides a wireless network for the entire system, allowing cameras, mobile devices and servers to communicate with one another (Famila et al., 2020).

Camera module: under the control of the timer, the camera takes pictures of the students in the classroom at regular points, names the pictures in a set format, stores them in the path set by the server and uploads the detailed information of the pictures to the server database (Malone, 2019).

Student APP: the router completes the attendance check on the device’s entry and exit. In addition, the APP can view all of its course information, view the camera pictures to complete the second precise attendance, receive the course change information, view the historical attendance records and view the course operation scores of each semester.

Teacher app: teachers can log in to the teacher app to add, delete, modify and check the courses taught, and they can view all student attendance records and course conduct scores for the courses.

Teacher computer: after the student completes the second sign-in on the mobile phone, the teacher has the opportunity to display the sign-in status of all students. Each seat in the classroom bears the name of the student. The student can check their attendance status, and the teacher can also have more interaction with the student in the classroom. If the student’s mobile device fails in attendance, he/she can apply to the teacher for attendance. After confirming the student’s identity, the teacher submits the student’s attendance information to the server to complete the auxiliary attendance.

2.1 Function Module

Wireless router attendance module

As the gateway layer of the entire system, the wireless router is responsible for the identification of mobile devices, the judgment of entering and leaving the classroom, the recording of attendance time and the transmission of attendance data. The MAC address is used as a unique identifier for each device, which can be associated with the MAC information of the student and the mobile phone. Moreover, the student’s identity can be confirmed by obtaining the MAC information of the device (Eaton & Mike, 2017). In this system, a wireless router installed with the Openwrt system is used to capture the detection request frame sent by the device at the system data link layer. In addition, the MAC information can be parsed according to the frame format. Figure 1 shows the wireless network structure model of this system.

When the server needs to interact with itself or other modules, there are two main methods: the first method is to establish a short connection M. Other modules actively call the external open interface of the server to query whether there are data to be transmitted, and the short connection is suitable for multi-user operation, thereby reducing the delay time of data transmission. The second method is to establish a long connection. When the server has data that needs to be transmitted to other modules, the server pushes the data to the relevant modules through a long connection. In addition, we send data regularly and keep the long connection unbroken to ensure that the long connection is not broken (Lai, & Hwang, 2016). According to the actual situation of this system, we choose to use a short connection to meet the needs of multiple users. Figure 2 presents a diagram of the server architecture.

2.2 Design and Implementation of Router Intelligent Attendance

The design of the router attendance record mainly records the time when students get in and out of class, generates attendance information and stores it in the database; the timer controls the camera to take pictures during class time and save the pictures in the database; the server calculates the student’s
course conduct scores according to the router’s attendance data and crops the pictures taken by the camera according to the student’s mobile phone sign-in position (Thai, Wever & Valcke, 2017). This case makes the traditional classroom attendance more streamlined, standardised and all-round classroom management. Figure 3 shows the data processing relationship between each summary.

The GL.iNET router is used, and the Openwrt system is installed for secondary development. The mobile terminal device connects to the router’s LAN and sends a probe request frame every 10 seconds. After the router AP receives the probe request frame ProbeRequest, it obtains the MAC information by parsing the frame. Then, it creates a message queue, sends the MAC information to the queue and waits for the main process to receive it. The main process traverses the scan status linked list every 10 seconds to determine whether the student is in the attendance or sign-out state (Zuber, 2016). After meeting the requirements, it generates attendance or sign-off information, which uses CURL to send the information to the server, and the server stores it in the attendance information table signinfo in the database. The router obtains the mobile phone MAC information and generates attendance information, as shown in Figure 4.

The main process creates a message queue and receives messages from the message queue. When receiving the MAC information sent by the hostpad, we traverse the linked list of related information to obtain the student ID corresponding to the MAC information (Rebeca, Vieira & Jeovani, 2016). The handle_hook function is used to update the scan state-linked list and traverse the scan state-linked list. By comparing the student ID information, it queries whether the entire node has the attendance record of the student ID. If not found, then a new attendance record is added at the end of the linked list; if found, then the status to IN is modified, which means that the student is still in attendance status. Figure 5 shows the identification of students and the detection of entering and leaving the classroom.
2.3. LEACH Agreement

LEACH protocol, the full name of ‘Low Energy Adaptive Clustering Hierarchy’ (Low Energy Adaptive Clustering Hierarchy), is a hierarchical routing protocol for wireless sensor networks. The LEACH protocol mainly uses the method of dynamically selecting cluster heads to realise the split processing of the total energy required for communication tasks, so that the nodes in the network have the opportunity to take on more tasks (Gough et al., 2017). The innovative point of its idea is to update the network cluster heads at all times and evenly distribute the energy that needs to be consumed to each node, to alleviate the pressure of individual nodes and achieve the effect of extending the life of the network. A round of the LEACH protocol includes two stages: cluster establishment and data transmission. The cluster establishment process is as follows: each node randomly generates a number between 0 and 1, and if the generated random number is less than the given threshold Ti, then the node will be elected as the cluster head (Asiksoy & Zdamli, 2016). Ti is generated by Eq. (1).
In the formula, \( r \) represents the current number of rounds, \( p \) represents the percentage of the number of cluster heads to the number of all nodes and \( G \) represents the set of cluster head nodes that were not elected in the previous \( r \mod (1/p) \) round. \( T_i \) represents fixed threshold. In the cluster establishment phase, the elected cluster head broadcasts messages, and other nodes are not selected as cluster heads. It judges the distance to the cluster head based on the speed and intensity of the

\[
T_i = \begin{cases} 
\frac{p}{1 - p \times (r \mod (1/p))}, & i \in G \\
0, & \text{otherwise}
\end{cases}
\]  

Figure 4. Attendance infographic

Figure 5. Judgment of entering and leaving the classroom
received message and then responds to the request to join the message to complete a stage. Then, the cluster head sets up a TDMA transmission data table for each node (DeRuisseau & Lara, 2016). After that, in the data transmission stage, the node completes the second round of tasks according to the TDMA table. Figure 6 shows the flow chart of the LEACH algorithm round.

2.4 Demonstration of the Key Points of the Improved Leach Protocol

Figure 6. Algorithm flow chart of LEACH agreement
2.4.1 Cluster Formation Stage

Based on the original LEACH protocol, each node randomly selects a number between 0 and 1, and when this number is less than a given $T_i(n)$, it is elected as the cluster head. However, to make the network obtain several relatively uniform clusters with lower energy consumption, the improved LEACH protocol formula is shown in Eq. (2).

$$T_i(n) = \begin{cases} \frac{p}{1 - p \times (r \mod (1/p))} \times \frac{E_n}{E} \times \frac{1}{p(n)}, & i \in G \\ 0, & \text{otherwise} \end{cases}$$ (2)

In the formula, $p = 1 / K_{opt}$ represents the completed round, $E_n$ represents the remaining energy of the $n$th node, $E$ represents the average energy of the surviving nodes and $(n)$ represents the sparsity of node distribution. The improved algorithm introduces an energy factor in $T_i(n)$, so that when the average energy of the network is relatively low, the number of rounds performed in a cycle is $1/P$ of the original algorithm. Moreover, by multiplying by a factor of $E_n / E$, the probability of high-energy nodes being elected as cluster heads is increased, thereby effectively protecting nodes with lower energy and avoiding their premature death. When the network model has been given, its $P$ value selection can be obtained by Eq. (2):

$$p = \sqrt{\frac{N_{\text{total}}}{2\pi} \times \frac{D_{\text{th}} \times M}{d^2} / N_{\text{total}}}$$ (3)

in

$$D_{\text{th}} = \sqrt{\frac{E_n}{E_f}}$$ (4)

The scale that the model can be magnified in the three-dimensional space is represented by $E_n$, and the scale that can be magnified under the multipath attenuation standard is represented by $E_f$. Moreover, the final result $D_{\text{th}}$ is the critical distance between the two. The selection of $K_{opt}$ value can be obtained by Eq. (5):

$$K_{opt} = \sqrt{\frac{N}{2\pi} \times \frac{\in \text{fs} \times M}{d^2 \text{to BS}}}$$ (5)

The average energy $E$ in Eq. (3) can be obtained by referring to the following method: the total energy value of all nodes in the cluster and the total number of nodes in the cluster can be added to the data message information sent by the cluster head to the base station. After the base station node receives the data messages from these cluster heads, it calculates the total value of the number of nodes and the total value of the node energy. Then, the division operation obtains the required $E$. Then, the message of $E$ is notified by broadcast, and the nodes in the area can know $E$. This method of calculating the average energy of all nodes in the station is simple and energy-saving. Thus, the required overhead is almost insignificant relative to the overhead of each data message transmission. The calculation formula of node density is defined as shown in Eq. (6):
\[ p(n) = \frac{N(n)}{N} \]  \hspace{1cm} (6)

### 2.5 Random Matrix Theoretical Model

In the wireless cognitive sensor network, as the secondary user, the wireless sensor node must use the channel resources of the primary user without hindering the normal work of the primary user. Therefore, the wireless sensor node needs to perform spectrum sensing to detect the channel. Assuming that the \( j \)th signal detected by node \( i \) performing spectrum sensing on the channel is:

\[ r_{ij} = \alpha \cdot s_{ij} + \beta \cdot n_{ij} \]  \hspace{1cm} (7)

Amongst them, \( \alpha \) (SNR) represents the signal-to-noise ratio, and \( s_{ij} \) represents the signal transmitted by the primary user.

\[ \mu = \sup \{10 \log_{10} \beta\} \]  \hspace{1cm} (8)

Spectrum sensing is to perform the following hypothesis tests based on the received signal:

\[ h_0 \hspace{0.5cm} s_{ij} = 0 \left( \text{The main user does not exist} \right) \]  \hspace{1cm} (9)

\[ h_1 \hspace{0.5cm} s_{ij} \neq 0 \left( \text{Master user exists} \right) \]  \hspace{1cm} (10)

In the cooperative spectrum sensing system, assuming that the information fusion node for spectrum sensing collects the information of \( K \) detection nodes, and each detection node has \( N \) detection data, at the information fusion node, a random matrix of \( K \times N \) can be formed \( H \). According to whether the main user exists, the random matrix \( H \) has different representations.

\[ H = \sum_{i=1}^{K} \sum_{j=1}^{N} \left( r_{ij} \cdot r_{ij}^H \right) \]  \hspace{1cm} (11)

The random matrix can form a Wishart matrix \( W \)

\[ W = HH^H, K \leq N, \]  \hspace{1cm} (12)

Amongst them, \( H^H \) represents the transposition of the \( H \) matrix. Here, we assume that the number of detection nodes \( K \) is less than the number of data detected by each node \( N \).

For Wishart matrix \( W \), we can find its eigenvalues, arranged in descending order, and its eigenvalues can be expressed as follows:

\[ \lambda_1 \geq \lambda_2 \geq \lambda_k > 0 \]  \hspace{1cm} (13)

The sum of all eigenvalues of the matrix is as follows:
The Maximum Minimum Eigenvalue detection method and the specific detection steps are as follows:

1. The sum of all eigenvalues of the matrix is as follows:

   $$T = \sum_{i=1}^{K} \lambda_i$$  \hspace{1cm} (14)

2. Getting the maximum eigenvalue $$\lambda_{\text{max}}$$ and minimum eigenvalue $$\lambda_{\text{min}}$$ of the matrix

3. Making a judgment, if $$\frac{\lambda_{\text{max}}}{\lambda_{\text{min}}} > \gamma_1$$, then it is considered that the main user exists; otherwise, it is considered that the main user does not exist, and $$\gamma_1$$ is the judgment threshold.

2.6. Distribution Function of DCN

The distribution function of DCN needs to be obtained first to use DCN for cooperative spectrum sensing.

$$f_{\text{DCN}}^R(x) = J_D x^{1-N^2} (x^2 - N)^{\frac{N(N+1)-4}{2}} F_2^1 \left( \frac{N-1}{2}, \frac{N+2}{2}, \frac{N^2 + N - 2}{2}, -(x^2 - N) \right)$$  \hspace{1cm} (16)

The coefficient $$J_D$$ is defined as follows:

$$J_D = \frac{2N\Gamma\left(\frac{N-1}{2}\right)\Gamma\left(\frac{N^2}{2}\right)}{\sqrt{\pi}\Gamma\left(\frac{N(N+1)-2}{2}\right)}$$  \hspace{1cm} (17)

$$\Gamma(\cdot)$$ is defined as the gamma function, and $$2F_1(\cdot)$$ is the hypergeometric distribution function.

$$f_{\text{DCN}}^C(x) = 2N (N^2 - 1) x^{1-2N^2} (x^2 - N)^{N^2-2}$$  \hspace{1cm} (18)

Using Mellin transformation, the PDF expression of any dimensional Wishart matrix DCN is also given:

$$f_{\text{DCN}}(x) = \Gamma\left(\frac{m}{2}\right) \sum_{i=0}^{(N-K)K} \frac{D_{(K,N)}(i - (N - K - 1))x^{-m/2}}{\Gamma\left(\frac{m}{2} - i - 1\right)(x-K)^{i+2-m/2}}$$  \hspace{1cm} (19)
3. DESIGN OF FC

The research is carried out around the following four questions:

What is the current situation of student autonomy in college English FCs? What are the problems? What are the reasons for the problems of student autonomy in the current college English FC? Is there a positive correlation between student autonomy and the effectiveness of college English FC teaching? How to improve student autonomy in college English FCs?

3.1. Object

In this study, a total of 104 students in four classes of non-English majors in a university’s sophomore year were taught English under the FC teaching model for one semester. Students are already familiar with the FC teaching model, and after the end of the semester, questionnaire surveys and interviews will be conducted for this group of students.

3.2. Method

In this study, a semester of college English FC teaching was conducted in the subjects’ classes. For 4 hours a week, the teacher used the supporting related learning CDs and online learning platform to assist in teaching. Teaching mode: in the pre-class stage, teachers issue learning tasks to students, and students log on to the online learning platform for autonomous learning, complete the learning tasks autonomously through the supporting CD and the PPT provided by the teacher and record the problems they encounter. During class, around unit topics, teachers design corresponding classroom activities, and students participate in classroom activities through cooperative learning and other methods and solve the remaining problems before class. After class, students independently or in group work to produce PPT and other materials to report their results in the next class.

3.3. Reliability Analysis

This paper used the questionnaire survey method to conduct research. In a sophomore college English FC implementation class, 50 students were randomly selected to give out the questionnaires, and all 50 were returned. The recovery rate is 100%. The respondents answered based on their own real experience, and no time limit was set. The ‘reliability’ in empirical research refers to whether the methods, conditions and results adopted by the research can be repeatedly verified, and whether the research results are consistent. In this study, the Cronbach’s coefficient in the ‘metric-reliability’ analysis in SPSS software was used to test the overall reliability of the self-made questionnaire. This coefficient is recognised as the most commonly used scale reliability test method. The Cronbach coefficient is mainly used to measure the consistency of the scores amongst the items in the scale, and it is suitable for attitude, opinion questionnaires or scale reliability analysis. The value of this coefficient is generally distributed between 0 and 1.

As shown in Table 1, the Cronbach coefficient value of the College English FC Student Autonomy Scale is 0.743, which is between 0.7 and 0.8, which has considerable credibility. Figure 7 shows the analysis of the Lambakh coefficient value (Hanson & Julie, 2016).

The ‘validity’ in empirical research refers to the degree to which the results of the research (intrinsic validity) and the universality of the conclusions of the research (external validity) can be clearly explained. Intrinsic validity refers to the degree to which the results of the study can be clearly explained, whereas external validity refers to the degree to which the results of the study can be applied to other group conditions, time and background (Liou, Bhagat & Chang, 2016). The content validity of a measurement scale usually depends on two factors: Firstly, when formulating the content, the content that needs to be tested must be included in the scope of the establishment;
secondly, the content of the determined item can show the main part of the variable that needs to be tested, and the main and minor parts are owned appropriate ratio. According to the three types of autonomy of cognition, emotion and behaviour in the scale, the total scale is regarded as composed of three-dimensional subscales. In addition, the correlation between the three subscales and the total scale is detected. Whether the items set in the self-made scale can reflect the content to be measured without repetition can be concluded. The correlation analysis between the three subscales and the total scale is carried out, and the correlation coefficient between each subscale and the total scale is obtained. Table 2 shows the results.

Table 2 shows that the correlation coefficient between each subscale is less than 0.5, which is a low correlation state. The correlation between each subscale and the total scale is greater than 0.65, indicating that the correlation is relatively high. This result shows that this scale measures the self-nature of students by three dimensions, and each dimension reflects an aspect of autonomy and represents one aspect of the overall level, which also proves that the scale has good validity.

### 3.4 Data Collection and Statistics

In this survey, a sample of non-English majors in their sophomore year at a university was selected. Four natural classes with English FCs were randomly selected for the survey, and the four classes had
a total of 104 students. As the questionnaires were distributed in the classroom, all 104 questionnaires were recovered, and the recovery rate was 100%.

A manual scoring method is used for the questionnaire results, calculating the total score of all students’ questionnaire results and entering the scores into EXCEL. Through the descriptive analysis in the SPSS software, the obtained data are analysed preliminary, and the distribution fluctuations of the level of autonomy in the student population are observed through the standard deviation and use the same method to analyse the scores of students in the three subscales. SPSS software spearman same–different order is used to measure the correlation between the student total table score and the final English score, obtain the sig value and judge the correlation. Moreover, the performance scores were correlated with the scores of the three subscales (Kostaris et al., 2016).

Through the statistics of the total scores of the surveyed students, we can get the overall situation of student autonomy in college English FCs. Firstly, according to the questionnaire content and the grading standard in the answer options, the total score of the questionnaire is divided into five score intervals (the total score of the autonomy scale is 150 points). Through SPSS software analysis, Table 3 shows the autonomy scores of sample students.

According to the statistics of the COUNTIF and SUMPRODUCT formulas in the EXCEL software, Table 4 shows the distribution of the number of students in each score interval of student autonomy.

Table 3 shows that the minimum score of student autonomy in college English FC is 49 points, with an average of 1.63 points for each question, and the level of autonomy is ‘very poor’. The highest score is 124 points, the average score for each question is 4.13 points and the level of autonomy belongs to the ‘good’ level. The overall student autonomy is divided into 91 points, with an average score of 3.03 points per question, and the level of autonomy is at the lowest level of ‘medium’ level.

From the sample distribution in Table 4, the samples are mainly distributed in the sub-segment areas with poor and medium autonomy. The number and proportion of those who failed in autonomy were 3, accounting for 3.19%. Moreover, the number of people in the two sub-segments accounts for 87.23% of the total sample number. The autonomy of students in college English FCs is generally in the poor and medium range, whereas the number of people with good autonomy only accounts for 9.57% of the total sample number. The sample with good autonomy is 0%. The majority of college English FC students have good autonomy, while those who fail or are excellent are few.

Table 2.
Correlation matrix between the various scales and the total scale

<table>
<thead>
<tr>
<th></th>
<th>Cognitive autonomy</th>
<th>Emotional autonomy</th>
<th>Behavioural autonomy</th>
<th>Total table</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive autonomy</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotional autonomy</td>
<td>0.334</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioural autonomy</td>
<td>0.402</td>
<td>0.462</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Total table</td>
<td>0.653</td>
<td>0.766</td>
<td>0.811</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 3.
Descriptive statistics of student autonomy questionnaires in college English FC

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomy analysis</td>
<td>94</td>
<td>49</td>
<td>124</td>
<td>91.00</td>
<td>14.986</td>
</tr>
<tr>
<td>Valid N (list status)</td>
<td>94</td>
<td>38</td>
<td>135</td>
<td>78</td>
<td></td>
</tr>
<tr>
<td>Behavioural autonomy</td>
<td>94</td>
<td>27</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive autonomy</td>
<td>94</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The experiment carried out descriptive statistics of the relevant values of cognitive autonomy, emotional autonomy and behaviour autonomy to better explore the in-depth situation of student autonomy. The objective is to find more relevant situations of student autonomy. Table 5 shows the descriptive statistics of each subscale score through SPSS software.

Table 5 shows that the maximum, minimum and average values of cognitive autonomy are slightly higher than emotional autonomy and behavioural autonomy, whereas the maximum, minimum and average values of emotional autonomy are higher than behavioural autonomy. Standard deviation comparison: the standard deviation value indicates the degree of dispersion of all values in a group of data relative to the average value. As the total scores of the three subscales are all 50 points, the degree of dispersion can be compared directly by the value of the standard deviation. The degree of dispersion of sample scores can be obtained by comparing the standard deviations of the three subscales: cognitive autonomy (4.974) < affective autonomy (5.113) < behaviour autonomy (5.420).

For further analysis, the six factors of autonomy in the three dimensions are descriptively counted, as shown in Table 6.

Table 6 shows the two factors in the dimension of cognitive autonomy: the minimum score for ‘self-monitoring’ factors is 9 points, and the average score for each question is 1.8 points, which belongs to the ‘very poor’ level of autonomy. The highest score is 24 points, and the average score for each question is 4.8 points, which belongs to the ‘very good autonomy’ level. The overall average of this factor is 16.97 points, that is, the average of each question is 3.39 points, and the overall situation of ‘self-monitoring’ factors is ‘medium level’. The minimum score of ‘self-feedback’ factor students is 7 points, and the average score for each question is 1.4 points, which belongs to the ‘very poor’ level of autonomy. The highest score is 21 points, and the average score for each question is 4.2, which belongs to the ‘good’ level of autonomy. The overall average score of this factor is 14.71 points, and the average score for each question is 2.94 points, that is, the overall situation of the ‘self-feedback’ factor is at a ‘poor’ level. Figure 8 shows a comparison chart describing the six factors.

The data in Figure 9 show that the distribution of student autonomy levels in the three dimensions is similar. In each dimension of autonomy, students are mainly distributed at the ‘poor’ or ‘medium’ levels, some are at the ‘very poor’ level, a few are at the ‘good’ level and the number of students at the
‘very good’ level is 0. However, in the dimension of cognitive autonomy, the distribution of students at the ‘poor’ and ‘medium’ levels is more balanced, whereas in the two dimensions of emotional and behavioural autonomy, more than 50% of the students are distributed at the ‘poor’ level.

From Figure 10, at the ‘very poor’ level of autonomy, the ‘strategy use’ factor has a large number of people, accounting for 11.7% of the total number, whereas the other five factors have a distribution rate of less than 5% at this level. At the ‘poor’ level of autonomy, the distribution rate of the ‘self-monitoring’ factor is 28.72%, and the other five factors are all higher than 50%. Amongst them, the distribution rate of the two factors of ‘strategic use’ and ‘self-feedback’ is higher than 60% here. At the ‘medium’ level of autonomy, the number of ‘strategy use’ factors is less distributed, only 12.77% of the total number of people, and the number of the other five factors accounted for approximately 30% of the total number of people. In the ‘good’ level of autonomy, the distribution rate of the ‘self-monitoring’ factor is 25.53%, and the distribution rate of the other five factors is less

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### Table 6.
**Descriptive statistics of six factors**

<table>
<thead>
<tr>
<th></th>
<th>( N )</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-monitoring</td>
<td>94</td>
<td>9</td>
<td>24</td>
<td>16.97</td>
<td>3.078</td>
</tr>
<tr>
<td>Self-feedback</td>
<td>94</td>
<td>7</td>
<td>21</td>
<td>14.71</td>
<td>2.448</td>
</tr>
<tr>
<td>Learning motivation</td>
<td>94</td>
<td>7</td>
<td>22</td>
<td>15.30</td>
<td>3.182</td>
</tr>
<tr>
<td>Interpersonal relationship</td>
<td>94</td>
<td>8</td>
<td>21</td>
<td>15.12</td>
<td>2.341</td>
</tr>
<tr>
<td>Strategy use</td>
<td>94</td>
<td>6</td>
<td>23</td>
<td>13.79</td>
<td>3.295</td>
</tr>
<tr>
<td>Study-time</td>
<td>94</td>
<td>8</td>
<td>21</td>
<td>15.12</td>
<td>2.647</td>
</tr>
<tr>
<td>Valid ( N ) (list status)</td>
<td>94</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

**Figure 8.**
**Description and comparison of six factors**
than 20%. Amongst them, the distribution rate of the two factors of ‘self-feedback’ and ‘interpersonal relationship’ is hovering at 7%. In the level of autonomy ‘very good’, the distribution rate of the ‘self-feedback’ factor is 7.45%, the distribution rate of the ‘learning motivation’ factor is 2.13%, the distribution rate of the ‘strategy use’ factor is 1.06% and the rest are all 0%.
4. DISCUSSION

In summary, the situation and problems of student autonomy in all dimensions can be drawn. Next, this paper would discuss the current situation and problems of understanding autonomy, emotional autonomy, and behavioral autonomy.

4.1. Recognise the Situation and Problems of Autonomy

The distribution of students is consistent with the autonomy of the total students, and the students who recognise autonomy are on average at the ‘medium’ level. Amongst them, the cognitive autonomy of individual students (3.19%) is ‘very poor’, and students at the ‘poor’ and ‘medium’ levels still account for more than half of the total number of students (79.79%). Compared with the overall student autonomy, the proportion of the ‘good’ number increased slightly, reaching 17.02% of the total number, whereas the ‘very good’ level coverage rate was 0%.

Students lack planning awareness, and through the feedback of ‘self-monitoring’ factor data, in college English FCs, most students cannot make relevant learning plans in the pre-class stage nor can they perform learning tasks according to the plan in the two links during and after class. Students lack the perseverance to study, for they cannot effectively monitor their learning behaviour during class and cannot continue to complete the learning plan after class (Chi, 2017). Students lack the ability to self-assess and correct. Moreover, through the feedback of the questionnaire results of the ‘self-feedback’ factor, most students will not regularly self-assess all aspects of their learning in the three stages of college English FCs nor will they reflect on their own learning effects.

4.2. Emotional Autonomy Situation and Problems

The distribution of students is consistent with the autonomy of total students, and the overall average of students with emotional autonomy is at the ‘medium’ level. Amongst them, the emotional autonomy of individual students (4.62%) is ‘very poor’, and students at the ‘poor’ and ‘medium’ levels still account for the vast majority of the overall students (86.17%). The proportion of ‘good’ students is the same as the overall student autonomy, reaching 9.57% of the total number of students, whereas the coverage rate of the ‘very good’ level is 0%, and students’ learning motivation is weak. As college English FC students have low expectations for their English learning before class, lack of learning motivation, and are unable to stimulate students’ high-quality autonomy, students should exercise in expression and communication. According to the survey results of the ‘learning motivation’ factor in the questionnaire, students in the college English FC have low expectations of their own English learning before class, and lack of learning motivation, which cannot stimulate quality student autonomy. Students are not good at expressing and communicating. Moreover, according to the survey results of the ‘interpersonal relationship’ factors in the questionnaire, in the middle part of the college English FC, students lack the enthusiasm to interact with teachers and classmates and are unwilling to actively seek help from teachers or classmates when encountering problems (Shaffer, 2016).

4.3. Behavioural Autonomy and Problems

The distribution of students is consistent with the autonomy of total students, and the students with behavioural autonomy are on average at a ‘poor’ level. Among them, the behavioural autonomy of individual students (4.62%) is ‘very poor’. The relative proportion of autonomy is similar, accounting for 8.51% of the total number of people, and the coverage rate of the ‘very good’ level is 0%. The use of learning strategies by students is low. According to the survey results of the ‘strategy use’ factors in the questionnaire, in the process of self-learning before the college English FC and the production of the after-class task results report, students will rarely choose suitable learning methods or adopt corresponding strategies to improve their learning effects. Students are confused about the schedule of study. Moreover, according to the survey results of the ‘study time’ factor in the questionnaire, students lack awareness of the overall planning of
study time in the pre-class part of the college English FC. In the after-school link, students also have a certain degree of procrastination, and few students will take the initiative to find their golden study time.

5. CONCLUSION

The article first made some innovations from the perspective of the research problem. When the FC teaching model is emerging, combined with the form of college English curriculum reform, this study discusses the college English FC teaching model and elaborates on its internal structure. The author chooses to study the issue of student autonomy in college English FCs not only because predecessors have not done in-depth research on this issue but also because the characteristics of college English FCs determine the important position of student autonomy in it. Based on the original research, combined with the characteristics of English learning autonomy and FC teaching mode, the autonomy of students in the college English FC is divided into dimensions. In addition, the factors under the dimensions are classified, trying to examine the current situation and problems of student autonomy from all dimensions. The survey found that the respondents have poor student autonomy during the implementation of college English FCs. They have the following problems: understanding autonomy: students have weak planning awareness, weak learning perseverance and lack of self-assessment and self-correction abilities; in emotional autonomy: students have weak learning motivation, a lack of active expression and communication skills; in behavioural autonomy: students use learning strategies less frequently, and their learning schedules are chaotic. The main reasons for the problem are as follows: In autonomy of cognition: students have an unclear understanding of their own situation and are highly dependent on teachers; emotional autonomy: students are affected by external incentives, lack of internal learning motivation and lack of self-confidence; behavioural autonomy: students have weak executive ability and weak time concept. Through the analysis of the correlation between student autonomy questionnaire scores and students’ English performance, a significant positive correlation is found between student autonomy and the effectiveness of college English FC teaching. Measures to enhance student autonomy: under the macro environment, increase the promotion of FCs in society and schools, and deepen the reform of college English courses; in the micro environment, break away from the traditional classroom dependence and strengthen the sense of autonomy; pay attention to the psychological needs of students and promote harmonious interpersonal relationships; improve execution ability and develop good habits. Students should pay attention to the role of autonomy in the FC, try to reflect on learning and corresponding self-correction at every stage of the FC and gradually develop their own sense of autonomy. Teachers should first guide students to have a general understanding of English courses before starting the new course. At the beginning of the new semester, teachers can use PPT or video to show students the course content and assessment requirements of the semester so that students can understand the requirements of the English course the semester. Moreover, they should guide students to set a reasonable overall learning plan and learning goals for the semester based on their actual level of English foundation based on understanding the curriculum requirements and curriculum settings. Of course, this paper also has shortcomings. However, there are still shortcomings in this paper. There is no survey of teachers in the experiment, so special attention should be paid in the future work.

CONFLICTS OF INTEREST

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