International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 3161-3170

https://doi.org/10.70517/ijhsa463265

Research on the Development of a Music and Mathematics Statistics Integration Course for Preschool Education Based on the OBE Concept

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Abstract Based on the concept of OBE, this paper explores the data-driven learning behavior of preschool music students. A multi-dimensional data analysis framework based on learning engagement was constructed, covering four types of indicators: behavioral, cognitive, emotional, and social. Through the whole-process behavior log and multi-modal interaction data of the MOOC platform, combined with the logistic regression model and social network analysis method, the learner's input state and evolution law are dynamically identified. The empirical results show that the model has a good prediction effect on the shallow, middle and deep inputs, and the average F1 values of the molecular sets of shallow, middle and deep inputs are all above 0.6. The 250 students were divided into three types of prototypes, with Prototype 1 having a medium overall level of engagement (3.20 points), Prototype 2 having an overall level of medium to high (3.98 points), and Prototype 3 having a high overall level of engagement (4.59 points). In terms of behavioral engagement, there was the largest difference in the number of "mutual evaluations" (standard deviation of 32.58), the difference in the quality value of peer comments and the entropy of self-rated information under different learning themes was large in cognitive engagement, the proportion of positive comments in online learning was more in emotional engagement (mean was 0.62), the overall network density difference was small (standard deviation was 0.06), and the individual network difference was larger. The results of this study provide data-driven decision support for the precise teaching design and personalized intervention of preschool music courses.

Index Terms obe concept, preschool music program, learning engagement, social network analysis, logistic regression modeling

I. Introduction

Currently, there are some problems and challenges in the teaching of preschool vocal music program [1]. On the one hand, some schools pay too much attention to the cultivation of vocal skills and ignore the characteristics of preschool education, resulting in students being unable to apply what they have learned to practical work [2]-[4]. On the other hand, the teaching method is single and lacks pertinence, which makes it difficult to meet the learning needs of different students [5]. In addition, the curriculum is unreasonable and out of touch with the actual work, which is also the challenge facing the current preschool vocal music program [6], [7]. With the continuous development of the society and the continuous updating of the concept of education, preschool education is also constantly reforming and innovating, and the reflection and reform based on the concept of OBE has become an urgent need in the teaching of preschool vocal music curriculum [8]-[10].

OBE is a kind of outcome-based education concept that emphasizes the lifelong development of learners and the cultivation of practical abilities [11], [12]. In the teaching of vocal music courses in preschool education, the teaching method based on the OBE concept will focus on cultivating students' practical abilities and skills rather than just the transfer of knowledge [13]-[15]. By setting clear teaching objectives and evaluation standards, learners can better understand and master vocal skills and can apply what they have learned to actual singing [16], [17]. With the development of information technology, the application of data analysis technology in education has received widespread attention, and by combining it with the OBE concept of preschool music curriculum, it can not only clarify the teaching objectives, but also realize personalized teaching, rational allocation of teaching resources, teaching evaluation and so on based on the teaching objectives, which is of great significance for improving the quality of preschool music teaching [18]-[21].

In this paper, we firstly sorted out the teaching objectives of the preschool music course under the OBE concept, and collected students' learning behavior data based on the MOOC platform. Integrating Fredricks' cognitive input theory, a four-dimensional learning input analysis framework of "behavioral-cognitive-emotional-social" was constructed. With the help of the social network model, we analyzed the students' learning engagement in terms of overall and individual networks. We analyzed the data of 250 preschool education students in the class of 2023 as experimental subjects. The logistic regression model was used to categorize students according to their learning engagement, and the learning patterns of the three types of students were analyzed according to the identification criteria of each engagement dimension. Based on the social network analysis, the social input characteristics of students were revealed.

II. Analysis of data-driven learning behaviors under the OBE philosophy

II. A. Design of Instructional Objectives Based on the Concept of OBE

The OBE education philosophy is outcome-oriented, requiring that the setting of teaching objectives must focus on achieving specific teaching effectiveness. Under the guidance of this concept, teachers should closely integrate the professional cultivation objectives and graduation requirements, formulate course objectives, and refine the teaching objectives of each class. As the teaching process advances, teachers should make timely adjustments and optimizations to the teaching objectives according to the teaching effectiveness and students' ability level.

The main employment direction of preschool education majors is early childhood teaching positions. Therefore, students must have solid music literacy, master the basic theories and methods of music education, have an in-depth understanding of the principles and techniques of early childhood music education, and have high sight-singing and singing ability, arrangement and creation skills and piano improvisation accompaniment ability, so as to lay a solid foundation for the future engagement in early childhood music education.

The objectives of the Music Theory Sight Singing course are closely related to the graduation requirements, mainly in the areas of knowledge integration and teaching ability. Through the study of this course, students will be able to systematically master the basic knowledge of music, have a certain degree of sight-singing ability, initially master the rhythm and pitch control skills, and be able to use what they have learned in kindergarten teaching to play and sing, and to carry out and implement accompanying music activities.

II. B. Data Acquisition and Processing

In the context of digital transformation of preschool education teacher training, traditional teaching ability assessment relies on periodic assessment and subjective experience judgment. With the in-depth application of Mucous Class (MOOC) platform in the field of vocational education, its full-process behavioral logs, multidimensional interactive data and process evaluation system provide a new paradigm for cracking this problem.

In this paper, we design a student behavioral engagement analysis model, whose data are mainly derived from database data and log file data, and the specific data analysis process is shown in Figure 1, where the data are first standardized, and then the data from the two sources are integrated at the same time.

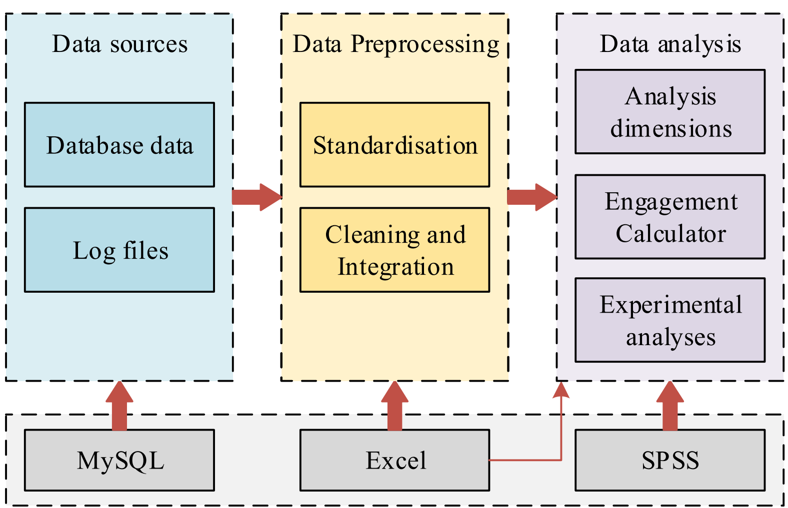

Figure 1: Data analysis process

In this paper, we select the course discussion forum data in the MOOC platform, and adopt the way of writing crawler code with the help of Python to collect all the data related to the discussion content and learner interactions in the discussion forum, and clean and process the data to prepare for the subsequent coding as well as analyzing of the data, and further subdivide the data collection and processing flow as shown in Figure 2.

Combined with the characteristics of text data in online learning discussion forums, the specific process of data collection and processing is as follows: filtering MOOC courses to collect discussion forum data through statistical MOOC course information; obtaining text data with the help of a crawler and arranging the acquired data into an Excel table; filtering and de-emphasis of the data as well as optimization of the data feature variables; analyzing learners' engagement in MOOC discussion forums in three aspects, namely, the behavioral dimension, the cognitive dimension and the interaction dimension. dimension, cognitive dimension and interaction dimension to analyze learners' engagement in MOOC discussion forums.

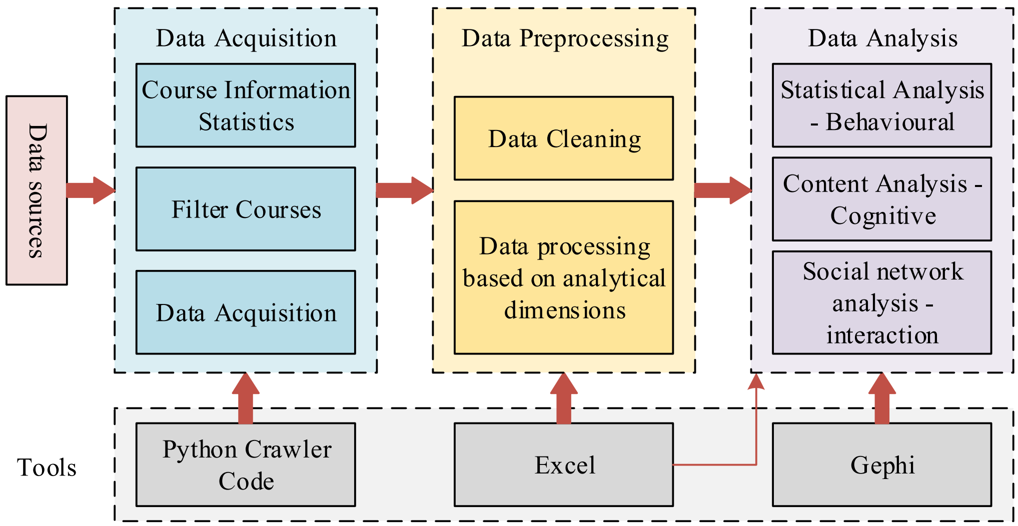

Figure 2: Data acquisition and processing flow

II. C.Analysis of learning engagement

II. C. 1) Behavioral engagement

Behavioral engagement is the actual action and level of participation demonstrated by students in the learning process, and is the basic vehicle for the other factors of student engagement. It includes learning behaviors such as participating in classroom activities, completing assignments, and actively participating in group discussions. Behavioral input is the most intuitive manifestation of students' learning process, and by observing the degree of students' participation and behavioral performance, we can initially assess their level of learning input in the classroom. Based on Fredricks' cognitive division theory, behavioral engagement is regarded as a key component of the student learning process, providing educators with observable data that help to provide a more comprehensive understanding of students' learning status.

In the MOOC platform, the entire process of a student's participation in a course will consist of nine specific learning behaviors, which are: class check-in, class tasks, class interactions, class resource events, discussion postings, comments, and likes. In this study, the sum of the occurrences of the above events in any one moment of a student's participation in a course will be used to represent a student's behavioral engagement at the current time in a course. Such a behavioral input situation can be represented by Equation (1).

$$beha\_enga^{T}=\sum_{k}^{n}\langle signIn,task,inter,res,diss,comt,like\rangle^{T} \tag{1}$$

where $beha\_enga^{T}$ represents the current moment T of the student's learning behavior, $signIn$ represents the event of the student's classroom check-in behavior, $task$ represents the event of the student completing the course tasks, $inter$ represents the event of the student completing the classroom interactions, res represents the event of the student completing the classroom resources related events (specifically: uploading resources, browsing resources, and downloading resources), $diss$ represents the event of the student completing the discussion posting event, $comt$ represents the event of the student completing the classroom forum commenting event, $like$ represents students' liking of classroom posts.

II. C. 2) Cognitive engagement

Cognitive input involves the process of thinking, understanding and applying knowledge as students learn. This level of input focuses on students' thinking activities, including their understanding of course content, demonstration of problem-solving skills, and the extent to which knowledge is applied. By assessing cognitive inputs, educators can gain a deeper understanding of the depth and breadth of students' learning and provide strong support for personalized instruction. When building an early warning model for teaching, the assessment of cognitive input can be obtained in a variety of ways, including quizzes, exams, and classroom interactions.

In the MOOC platform, students complete online quizzes in stages, and will get quiz scores according to the system or teachers' evaluation, and the scores can reflect to a certain extent the students' understanding and mastery of the knowledge and learning content at this stage; from the subjective level of the students, through the students' replies to the posts in the forums, the students' current knowledge of the course can be extracted according to the textual content of the students' knowledge of the course at which stage they stay. At which stage.

In order to get the students' cognitive performance, this study starts from Garrison et al.'s social constructivism, whose definition clearly explains the key factors affecting blended learning. According to the community model theory, social, pedagogical and cognitive presence are the three important factors that affect students' blended learning, and effective learning can only happen when all three types of presence are at a high level in a course. The component structure of the community model theory is shown in Figure 3.

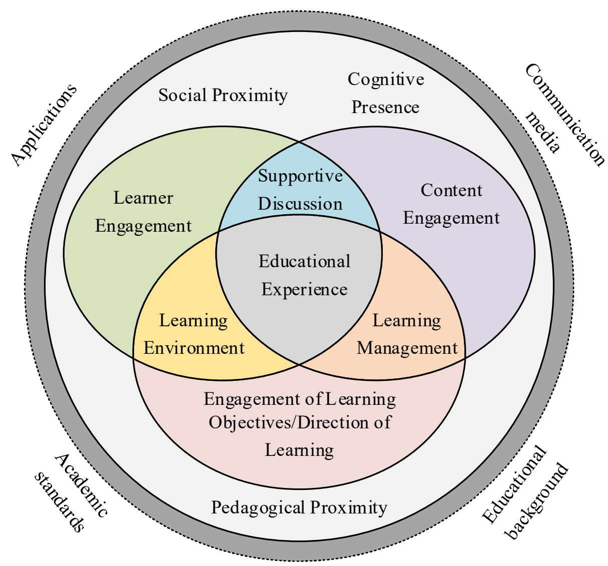

Figure 3: Community Model Theory

Among them, the creation of cognitive proximity includes four stages: triggering event, exploration, integration, and solution. Trigger event refers to arousing students' awareness of the problem and causing confusion about the knowledge; the process of exploration includes students disagreeing about the knowledge points, exchanging information, providing each other with suggestions, brainstorming, and drawing conclusions; integration includes several processes of converging conclusions, integrating viewpoints, and creating solutions; and solving includes the process of searching for an application, testing the application, and revising the application.

In this paper, we categorize the verbal text content of students in the MOOC platform forum by the above four events that form the cognitive proximity, so as to show the current cognitive stage of students. In addition, it is also necessary to set a separate cognitive situation as "other" to represent other situations that cannot be covered by the above four situations.

The combination of the above will result in the cognitive engagement of a student at the current time in a course. Such a cognitive engagement can be represented by equation (2).

$$cogn\_enga^{T} = \sum_{k}^{n} \langle score, spring, explore, integration, solve, other \rangle^{T} \quad (2)$$

where $cogn\_enga^{T}$ represents the student's cognitive engagement at the current moment T, $score$ represents the student's stage-specific test score, $spring$ represents the student's forum text as triggered, $explore$

represents the student's forum text as explored, $\mathrm{int}\,egration$ represents the student's forum text as integrated, $solve$ represents the student's forum text as solved, and $other$ represents the student's forum text as other.

II. C. 3) Emotional engagement

Emotional engagement involves the emotional experiences and attitudes of students in the learning process. This includes emotional dimensions such as students' level of interest in the subject, self-confidence, and subject identity. Understanding students' affective engagement helps educators to better meet their learning needs and create a positive learning environment. In the Teaching Alert Model, affective engagement can be assessed through questionnaires, feedback, and observation of students' expressions and engagement.

In previous research related to emotion and teaching, human emotion and mood are generally divided into three processes: subjective experience, physiological arousal, and external behavior. Among them, the subjective experience is a person in contact with a specific scene produced by a certain emotion, this process can only be perceived by the subjective level of the individual; physiological arousal is the physiological level of the person for the emotion to produce a kind of feedback, this process can only be detected with the help of a specific instrument; external behavior is a person with the help of the emotion of the objective world to produce certain behaviors, the process of the data can be obtained through the detection of the specific The data of this process can be obtained through the detection of specific behaviors. The common methods of assessing students' emotions are as follows: (1) emotional questionnaires (representing the process of subjective experience), (2) brainwave-related instrumentation (representing the process of physiological arousal), and (3) textual emotion detection (representing the process of external behavior).

From the above analysis, it can be seen that by extracting the textual speech of students in the forum in the intelligent teaching platform, it will be possible to get the current stage of the students' emotional and affective expression in the way of detecting the affective process of the students' external behavior. Such a cognitive input situation can be expressed by formula (3).

$$\begin{aligned} &emo\_enga^{T} \\ &= \sum\nolimits_{k}^{n} \langle admiration, amusement, anger, caring, fear, \cdots \rangle^{T} \end{aligned} \tag{3}$$

where emo_enga^{T} represents the student's emotional engagement at the current moment T, $admiration$, $amusement$, etc. represent the current student's performance of different types of emotions in the current learning stage.

II. C. 4) Social engagement

(1) Overall network analysis

Network density as a measure of the characteristics of the social network, can feedback the degree of association between the member objects in the network, the higher the density of the network on the attitude of the actors in it, the greater the impact on the behavior and so on. In the social network structure, the greater the network density, the closer the connection between the learners, the better the interaction atmosphere of the whole network, the more frequent the interaction, the network density analysis of the interaction behavior to find out the overall interaction of the social network and the individual network density of each learner.

The network density is divided into overall network density and individual network density, and the density D of the overall network and the density D_i of the individual network of the i nd learner are calculated in a very similar way, and the calculation process in the directed social network are equations (4) and (5), respectively:

$$D = \frac{M}{N} = \frac{M}{n(n-1)} \quad (n \neq 0,1) \tag{4}$$

$$D_i = \frac{M_i}{N_i} = \frac{M_i}{n_i(n_i-1)} \quad (n_i \neq 0,1) \tag{5}$$

M denotes the actual number of relationships contained in the overall network, N denotes the theoretical maximum number of relationships that could exist in the overall network, and n denotes that there are n member objects in this network structure. M_i denotes the actual number of relationships in the individual network of the i th member, N_i denotes the theoretical maximum number of relationships that could exist in the individual network of the i th member, and n_i is the size of the individual network of the i th member.

(2) Individual network analysis

Reciprocity is one of the indicators of individual social network characteristics, describing whether the relationship between members is mutual. In the forum network structure, the main actions include posting and replying to posts. Interaction in the forum is not instantaneous, that is, it occurs when a learner logs into the platform, enters the forum to view the posts posted by other learners as well as the replies to the posts, and is willing to actively reply to other learners. Therefore, interactions between learners in the forum are not necessarily reciprocal; learners posting posts may not necessarily receive replies from other learners, and interactions between learners may not take place in both directions.

Reciprocity is a description of the number of mutual interactions between learners, and in practice, reciprocity is often quantified by the reciprocity coefficient. Analyzing the reciprocity of learners can understand the mutual interaction between learners and the interaction pattern between the learner and other learners in the forum, combined with the results of the centrality analysis, to give some guidance to learners with low reciprocity. The reciprocity coefficient is calculated as formula (6):

$$R_D(Ni) = \sum_{k=1}^{n} r(Nij) / m \quad (i \neq j) \tag{6}$$

$r(Nij)$ denotes the number of mutual interactions between both node i and node j in the interaction network, and m denotes the total number of edges in the network.

III. Research on Data-Driven Teaching Models for Preschool Music Programs

This study was conducted at University A. The experimental population consisted of 250 preschool education students in the class of 2023. The preschool music course offered was a compulsory course, with 2 class hours per week and 16 weeks of instruction. The content of the textbook is accompanied by MOOC resources, with the 1st to 4th weeks being taught offline and the remaining 12 weeks being taught online through the MOOC platform, which provides a variety of multimodal and multilingual resources and clear teaching instructions, urging students to actively search for materials and solve problems they encounter in a timely manner.

III. A. Learning engagement evaluation model performance validation

Eleven feature indicators were screened from behavioral, cognitive, emotional, and social dimensions to create a learning input evaluation model.

Logistic regression (LR) utilizes regression algorithms to solve classification problems, mainly for dichotomous variables. The implementation is simple and efficient, the results are easy to interpret, the calculation is fast, and the possibility of classification can be modeled directly, avoiding the problems caused by inaccurate distribution of assumptions. To apply it to a multicategorization model, the multicategorization task can be split so that it becomes multiple categorization tasks. Assume that the final is a triple categorization result (A, B, C).

When the model parameters are determined (penalty="1", C=0.3, solver="liblinear"), the model subset is trained:

Subset 1: Top 5 variables in terms of correlation;

Subset II: Variables ranked in the top 7 for relevance;

Subset III: variables with top 9 correlations;

Full set: contains all variables.

Logistic regression model training was performed using the logistic regression classifier from the Sklearn library for Python. After reading the dataset, the data were uniquely hot coded and normalized to prepare for model training and divided into training and test sets according to the seventy-three score. The OVR training model is used to find the optimal C.

The training results of the logistic regression classifier based on this condition are shown in Table 1. As can be seen from Table 1, the model has a good prediction effect for shallow, medium and deep input degrees, and the average F1 values of the molecule set of shallow, medium and deep input degrees are 0.8612, 0.7903 and 0.7094, respectively, which are all above 0.6.

III. B. Learning Pattern Recognition

III. B. 1) Learning engagement prototype

The 250 students were divided into three types of prototypes based on the learning engagement evaluation model, and the classification results are shown in Table 2. As can be seen from Table 2, prototype 1, with a total of 88 students, accounting for 35.2%, has a medium level of overall engagement (3.20 points). It had the lowest level of social engagement (2.48 points). Prototype 2 had the highest number of participants, totaling 112, or 44.8%, with a medium level of overall input (3.98 points). Its behavioral, cognitive, and affective inputs were all higher than a score of 4. Prototype 3 had a total of 50 people, or 20%, and had a high level of overall engagement (4.59 points). None of the four engagement dimensions were below 4.5 points. Of the three types of prototypes, the emotional input level was the highest and the social input level was the lowest.

Table 1: Comparison of logistic regression classifier results

		Shallow investment ratio	Middle level engagement	Deep investment level
Subset 1	Precision	0.8658	0.7956	0.7155
	Recall	0.8533	0.7862	0.7081
	F1-score	0.8595	0.7909	0.7118
Subset 2	Precision	0.8613	0.7985	0.7056
	Recall	0.8655	0.7923	0.6983
	F1-score	0.8634	0.7954	0.7019
Subset 3	Precision	0.8535	0.7882	0.7103
	Recall	0.8601	0.7935	0.7159
	F1-score	0.8568	0.7908	0.7131
Complete set	Precision	0.8623	0.7786	0.7088
	Recall	0.8679	0.7895	0.7127
	F1-score	0.8651	0.7840	0.7107

Table 2: Prototype of Learner Engagement

	Prototype 1		Prototype 2		Prototype 3	
	M	SD	M	SD	M	SD
Behavioral investment	3.43	0.44	4.11	0.33	4.58	0.31
Cognitive engagement	3.38	0.38	4.08	0.29	4.55	0.27
Emotional engagement	3.49	0.41	4.14	0.35	4.62	0.33
Social engagement	2.48	0.55	3.58	0.37	4.59	0.32
Total investment level	3.20	0.36	3.98	0.35	4.59	0.21

III. B. 2) Learner input suction state and attractor identification

Based on the classification results and the identification criteria of each input dimension, seven types of suction states were identified, namely, positive behavioral and cognitive dominant input suction state, negative affective and cognitive dominant input suction state, negative social dominant input suction state, positive behavioral dominant input suction state, negative behavioral dominant input suction state, negative cognitive and social dominant input suction state, and positive behavioral and affective dominant input suction state. The seven suction states are numbered as A1~A7, and the results of learning input suction state visualization for the three types of prototypes are shown in Figure 4.

All three prototypes experienced negative social dominant input suction states 1 time each for a total of 8 weeks; positive behavioral and cognitive dominant input suction states had the highest frequency (4 times) and the longest duration (16 weeks); positive behavioral and affective dominant input suction states appeared only 1 time and lasted 10 weeks; positive behavioral dominant inputs, negative behavioral dominant inputs, and negative affective and cognitive dominant inputs suction states lasted 4 weeks, with a frequency of 1 to 2 times; the negative cognitive and social dominant input suction state occurred only once and lasted 2 weeks.

III. B. 3) Social Input Analysis

The social network was used to analyze the students' learning social inputs, and the overall network density was used as a measure of the overall network structure, which reflected the density of the interconnected edges between nodes in the network, and the specific operational steps for the analysis were (1) transforming the relational data of the online mutual evaluation of the preschool music course into the standard two-dimensional matrix data format of the Ucinet software, and (2) in the Netdraw software Perform the overall network structure analysis and get the visualization results. Some of the raw data transformed into matrix data are shown in Table 3, and the matrix data represent the number of times a student evaluated another student's work n times.

The five indexes of in-ness, out-ness, in-approach centrality, out-approach centrality, and intermediate centrality were calculated in Ucinet software for 250 students, and some of the results are shown in Table 4. Three representative learners, S1, S62 and S119, were selected from the 250 students to specify the differences in the structure of the individual networks of social engagement, based on the fact that these three students belonged to prototype 1, prototype 2, and prototype 3, respectively, and the following conclusions can be drawn in conjunction with Table 4.

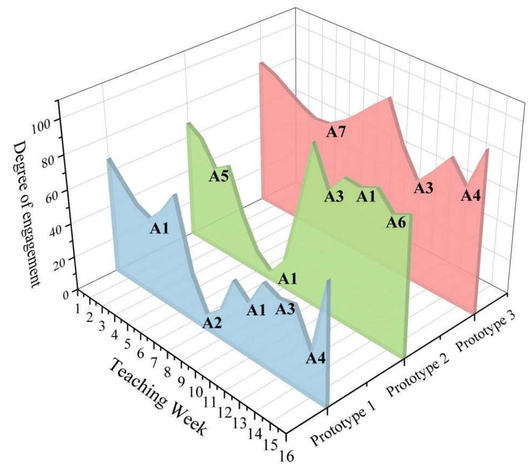

Figure 4: Learning input absorption states of the three types of prototypes

Table 3: Matrix Data Format(Part)

User ID	S1	S2	S3	S4	S5	S6	S7	S8	S9
S1	3	1	1	2	1	2	1	0	...
S2	1	0	1	2	1	0	1	2	...
S3	1	2	0	2	1	1	2	0	...
S4	2	1	0	1	0	1	2	0	...
S5	1	1	1	2	0	0	1	3	...
S6	3	1	0	0	1	1	1	1	...
S7	0	2	0	2	1		0	2	...
S8	1	1	1	2	1	0	1	0	...
S9	...	...	...	...	...	...	...	...	...

(1) Student S1 is significantly higher than other learners in the indexes of in-degree, in-approach centrality and intermediate centrality, which indicates that the student is in the middle of the social network, actively participates in online evaluation, and his work is highly concerned; in the indexes of out-degree and out-approach centrality, they are basically the same as that of student S62, which indicates that students in the high and intermediate levels of learning performance are capable of completing the evaluation tasks assigned by the teacher.

(2) Student S62 is at a medium level on the in-degree, in-approach centrality, and intermediate centrality indicators, which indicates that the student's social engagement is passive and less likely to establish close social connections with peers around him or her.

(3) Student S119 has the lowest values for each indicator of social engagement, with fewer evaluations and fewer evaluated, and is in a marginal position in the social network.

Individual network characteristics showed that evaluation tasks were largely completed by students at intermediate and above academic levels, with generally high out-degree and out-proximity centrality values. It was found that online evaluation social engagement was high and peer interaction relationships were frequent. This may be related to the random grouping function of the MOOC platform, which ensures the smooth implementation of online mutual evaluation activities by randomly dividing students into specific mutual evaluation groups. However, the overall network density, the number of edge members, and the number of core members varied across learning topics as the course progressed.

III. B. 4) Basic information on the level of learning engagement

The basic online evaluation inputs for the course are shown in Table 5. From the data, it can be seen that there are large differences in behavioral inputs, among which the “number of mutual evaluations” has the largest difference (the standard deviation is 32.58), and the maximum number of times learners evaluated each other in the tasks of a single topic was 468 times, and the minimum was only 135 times. In terms of cognitive input, from the maximum and minimum values, the difference in the quality value of peer assessment and the difference in the entropy of self-assessment information are large in different learning themes, which indicates that there is a difference in the overall level of cognitive input of students in different themes. In terms of emotional input, from the mean value, there are more positive comments in online learning (mean value of 0.62), while there are relatively fewer negative and neutral comments, which indicates that the overall emotional input is more positive in the peer-assessed learning of the course. In terms of social engagement, (1) the difference in overall network density was small (standard deviation of 0.06), with frequent evaluation interactions between students and tight evaluation social networks. (2) The structure of the group network showed a large difference in the composition of the number of core members and the number of fringe members across learning topics (standard deviation of 10.22), and there were differences in evaluative interactions between groups. (3) The individual network has a large difference, as can be seen from the maximum and minimum values of the out degree and the in degree, the students are in a wandering state during the online evaluation process and do not participate in the course evaluation activities.

Table 4: Comparison of individual network structure indicators(Part)

User ID	Degree of entry	Degree of out	Enter near centrality	Out close to centrality	Central centrality
S1	50	27	41.497	25.386	44.273
S2	38	36	30.974	25.967	33.286
S3	16	16	24.083	23.846	13.193
...	...	...	...	...	...
S62	23	26	22.487	24.896	18.973
S63	46	42	38.325	24.972	39.486
S64	12	11	18.486	24.386	7.947
...	...	...	...	...	...
S119	7	9	16.397	24.084	3.082
S120	13	14	23.697	25.084	15.397
S121	28	22	32.587	25.189	27.497
...	...	...	...	...	...

Table 5: Online evaluation input under different topic learning

<table>
<tr><th colspan="3">Indicator</th><th>Maximum value</th><th>Minimum value</th><th>Mean value</th><th>Standard deviation</th></tr>
<tr><td rowspan="3">Behavioral engagement</td><td colspan="2">Number of self-evaluation</td><td>33</td><td>25</td><td>24.69</td><td>1.46</td></tr>
<tr><td colspan="2">Number of mutual evaluations</td><td>468</td><td>135</td><td>278</td><td>32.58</td></tr>
<tr><td colspan="2">Degree of interaction</td><td>0.87</td><td>0.26</td><td>0.68</td><td>0.18</td></tr>
<tr><td rowspan="2">Cognitive engagement</td><td colspan="2">Peer review quality values</td><td>48.39</td><td>39.22</td><td>45.35</td><td>1.57</td></tr>
<tr><td colspan="2">Self-rated information entropy</td><td>156.35</td><td>104.68</td><td>133.53</td><td>12.79</td></tr>
<tr><td rowspan="3">Emotional engagement</td><td colspan="2">The proportion of positive comments</td><td>0.81</td><td>0.28</td><td>0.62</td><td>0.17</td></tr>
<tr><td colspan="2">The proportion of negative comments</td><td>0.44</td><td>0.16</td><td>0.26</td><td>0.09</td></tr>
<tr><td colspan="2">The proportion of neutral comments</td><td>0.32</td><td>0.08</td><td>0.15</td><td>0.12</td></tr>
<tr><td rowspan="3">Social engagement</td><td colspan="2">Overall network structure</td><td>0.38</td><td>0.02</td><td>0.15</td><td>0.06</td></tr>
<tr><td rowspan="2">Individual network structure</td><td>Number of core members</td><td>38</td><td>6</td><td>21.43</td><td>10.22</td></tr>
<tr><td>Number of marginal members</td><td>27</td><td>3</td><td>14.34</td><td>10.22</td></tr>
</table>

IV. Conclusion

Based on the four-dimensional learning behavior analysis framework of “Behavioral-Cognitive-Emotional-Social”, this paper explores the learning patterns of students in preschool music courses based on data analysis techniques.

The model was a good predictor of shallow, medium, and deep engagement, with average F1 values for the shallow, medium, and deep engagement molecule sets of 0.8612, 0.7903, and 0.7094, respectively, which were all above 0.6. The 250 students were classified into three types of prototypes, with prototype 1 having a medium level of overall engagement (3.20 scores), prototype 2 a medium-high level of overall engagement (3.98 scores) and Prototype 3 had a high overall level of engagement (4.59 points). All three prototypes experienced one negative social dominant input suction state each, lasting a total of 8 weeks; positive behavioral and cognitive dominant input suction states had the highest frequency (4 times) and lasted the longest (16 weeks); positive behavioral and affective dominant input suction states appeared only once and lasted 10 weeks; positive behavioral dominant inputs, negative behavioral dominant inputs, and negative affective and cognitive dominant inputs suction states lasted for 4 weeks, with a frequency of 1 to 2 times; the negative cognitive and social dominant input suction state appeared only once and lasted for 2 weeks. From the individual network characteristics, it can be seen that students with intermediate and higher academic levels basically completed the evaluation task, and the values of out-degree and out-proximity centrality were generally high.

The basic situation of online evaluation input shows that there is a large difference in behavioral input, with the largest difference in the number of mutual evaluations (standard deviation of 32.58), and the highest number of mutual evaluations in a single topic task is 468, while the lowest is only 135. In terms of cognitive input, from the maximum and minimum values, the difference in the quality value of peer assessment and the entropy of self-assessment information are large in different learning topics. In terms of affective input, there were more positive rubrics in online learning (mean value of 0.62), while there were relatively few negative and neutral rubrics. For social engagement, the difference in overall network density was small (standard deviation of 0.06), the difference in the composition of the number of core members and the number of fringe members across learning topics was large (standard deviation of 10.22), and the difference in individual networks was large.

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