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PAPER

Visual Interactive Mobile Analysis of Online English Learning Behavior Based on Lagged Sequence Analysis Approach

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ABSTRACT

As online education and visualization continue to advance, the volume of information is growing exponentially. However, the current intelligent system for online learning visualization is constructed with a relatively one-dimensional approach, leading to a one-sided optimization effect. Therefore, this study designs an efficient model for constructing learning paths for online groups from the perspective of blended learning, utilizing lagged sequence analysis (LSA). In addition, the model incorporates lagged sequence analysis, data mining methods, the minimum spanning tree algorithm, and other techniques to propose the OGLPM-S strategy. The experimental results demonstrate that the strategy is feasible, exhibiting high efficiency and stability. In addition, the intelligent joint algorithm can generate various group learning paths based on the characteristics of online English learners in the group. Through the novel LSA federation method, this paper establishes an online intelligent learning platform for group learning path construction services. It elaborates on the platform's overall architecture, functional flow, strategy implementation, and construction results. The results show that the LSA-OGLPM-S strategy proposed in this paper can successfully construct group learning paths based on the behavioral data of online English learners. This approach is suitable for facilitating online learning among English learners.

KEYWORDS

lagged sequence analysis method (LSAM), OGLPM-S strategy visualization, intelligent systems, multi-scale design, online English learning

1 INTRODUCTION

With the prevalence of online education and visualization development, the amount of information data is growing exponentially. By mining and analyzing online education data, we can uncover the significant value hidden within it [1]. In the context of "Internet +" education, online English education data has become a new element of teaching and learning. The development of online English learning

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behaviors and their visualization elements has become a core asset for analyzing student outcomes [2]. At the same time, the expansion of visual learning status tracking databases, combined with data analysis procedures, assists teachers in identifying patterns in learners' online English learning behaviors, predicting learners' performance and risks, and making timely and effective intervention adjustments. This enables personalized and visualized teaching possible [3]. Some scholars have discovered students' learning time preferences and online course module access preferences through learners' learning process data. Mining the association between learning behaviors and learning effects [4]. Learning behavior data is used to predict learners' learning outcomes, etc. Many existing studies related to the prediction of learning effectiveness [5–7] are based on data on learners' behavioral engagement during learning. the amount of effort and time learners invest in specific learning activities. These coarse-grained data do not reflect the learner's cognitive engagement level in detail, and some of the learning behavior data do not accurately predict learning outcomes. Recent studies have found that learning behavior sequences during the learning process better reflect learners' trajectories, willingness, and cognitive processes than student engagement. For example, learning behavior sequence analysis is used to study the behavioral patterns of the entire activity process as well as the behavioral patterns of different learning stages and to compare the behavioral patterns of various learning achievement groups. At the same time, by utilizing learners' learning behavior sequences to forecast their learning outcomes, teachers can identify the crucial behavior sequences necessary for monitoring and analyzing the learning process. This enables them to monitor learners' progress, promptly implement pedagogical interventions, and enhance learning outcomes [8].

Finding several learned behavior sequences that are significant can reveal patterns in learners' behaviors. The Lagged Sequence Analysis Method (LSAM) was first devised by Sackett [9]. It is primarily used to assess the likelihood of one event or behavior occurring before another behavior in people and to determine its statistical significance. Currently, LSA has been applied to analyze customer behavioral preferences in the sub-commercial field, study patient behavior and treatment in the medical field, and analyze player gaming behavior in the gaming field [10]. In recent years, researchers in the field of educational technology have started to focus on LSA and utilize it for research on analyzing learning behaviors. Hwang et al. applied LSA to study the behavioral characteristics of elementary school students using mind mapping tools to discover knowledge in geography courses [11]. Jeong utilized LSA to analyze the behavioral patterns of group interactions among graduate students in asynchronous discussion forums [12]. Hou et al. employed LSA to extract sequences of manipulative behaviors exhibited by elementary and middle school students in a role-playing game [13]. Eryilmaz et al. utilized LSA to examine the knowledge-construction behaviors of college students in online social interactions [14]. Yang et al. utilized LSA to compare the knowledge construction behavior patterns of college students at various collaborative stages during collaborative translation activities [15].

Lagged sequence analysis has promising applications in the field of learning behavior analysis. It can assist researchers and educators in accurately understanding the potential behavioral patterns of learners, explaining the reasons for technologically-enhanced learning effects from a behavioral perspective, and effectively guiding the design and implementation of subsequent teaching and learning activities. Since collaborative filtering algorithms have demonstrated good recommendation performance, they have also been widely applied in numerous applications in the field of learning path construction. Liu et al. [16] developed a collaborative filtering-based course recommendation method using learners' learning behavior data and included a keyword resource search function. Zha et al. [17], on the other hand, focused on students' learning progress and characterized the learning behaviors of vocational high school students to create a more personalized recommendation model using the collaborative filtering algorithm. Zhao et al. [18] enhanced the collaborative filtering recommendation algorithm by considering the absence of the current learning system from both the user and learning topic perspectives. They conducted relevant experiments to demonstrate the reliability and effectiveness of the enhanced algorithm. Li et al. [19] associated the learner information, knowledge point information, and learning resource data to create a multidimensional heterogeneous information matrix. This approach enhances recommendation accuracy by utilizing information-data similarity and score prediction to cater to the personalized learning needs of learners. Wang Yonggu et al. [20] proposed a resource recommendation model based on collaborative filtering technology to address the challenge of the low relevance of recommended learning resources in online learning. They recommended online learning resources with higher relevance to learners. Additionally, Wang Wei [21] analyzed the learning process data of online English learners, extracted implicitly useful data to enhance the scoring matrix, and applied the collaborative filtering optimization algorithm to achieve personalized recommendations. Personalized recommendation. Cai Qiang et al. [22] designed a collaborative filtering algorithm that effectively addresses the issues of cold-start and data sparsity to provide personalized learning recommendations and improve recommendation results. The collaborative filtering algorithm can be implemented without considering the user's feature representation, which reduces the complexity of the algorithm. However, when the interaction data between the learner and the learning resources is not available or the data is limited, the "cold-start" problem may significantly impact the performance of the recommendation. Chen et al. [23] integrated a genetic algorithm into an e-learning system to enhance the level of personalization. Chen et al. [23] integrated a genetic algorithm into an e-learning system to enhance the system's personalization degree. This algorithm can sort personalized courses by taking into account the difficulty level of the courseware and the conceptual continuity of the learning path. Tan et al. [24] integrated genetic algorithms into the process of creating and evolving online courses to achieve personalized learning for the learners. The proposed method primarily includes a generating module for course initialization and an evaluating module for course development, each consisting of two parts. The course's personalization is achieved based on the evaluation results of the students. Previous studies have overlooked the dynamic changes in learners' learning abilities. Dynamically, Li et al. [25] incorporated personalization factors into the e-learning process. This allows course generation to dynamically select learning resources based on learners' abilities and create personalized e-learning courses. They achieved this by utilizing an algorithm that is both fast and accurate. Chang et al. [26] integrated genetic algorithms into the course generation process to enhance the level of personalization of the course, which is accomplished by assessing the learners' abilities. Han et al. [27] utilized genetic algorithms to enhance the level of personalization in learning approaches. They tailored guidance based on individual learner differences, employing intelligent algorithms to deliver precise teaching. Lin et al. [28] utilized order preference technology to enhance the genetic algorithm and incorporated it into the learning management system to personalize teaching by designing the learning process. Dwivedi et al. [29] highlighted that the personalized e-learning recommender system should not only suggest unordered learning resources to the learner but, more importantly, it should arrange them after recommending resources to provide the learner with a sequence of organized learning resources, known as the learning path. To enhance learners' online learning outcomes, Yang and Wu [30] introduced an adaptive learning path recommendation method based on the graph-immunity algorithm. This method abstracts the learning path construction issue as a multi-objective combinatorial optimization problem using concepts and learners' data. It employs a joint approach to problem solving. Additionally, other scholars, including Hsu et al. [31], have adopted a data-driven perspective. They analyze the learning process data collected from the learning platform as the research focus. By utilizing lag sequence analysis, they investigate the order and logic of occurrences among various behaviors, ultimately creating learning path diagrams.

The aforementioned studies have enhanced the efficacy of constructing group learning paths to some extent [31–33]. However, the construction approach is relatively simplistic, leading to a cone-sided optimization effect. Moreover, there is a scarcity of studies focusing on optimizing models and conducting data analysis in conjunction with visualization. Therefore, this study proposes a visual analysis system for online English learning behavior based on the lag sequence analysis method and conducts relevant analysis and discussion.

2 ONLINE GROUP LEARNING PATHWAY CONSTRUCTION MODEL

The purpose of group behavioral sequence correlation analysis is to group learners based on learning process data and online English learner characteristics, calculate the probability of occurrence of behavioral sequences within the group, and determine whether there is a statistically significant relationship. This analysis mainly consists of two parts: clustering of online English learners and lagged sequence analysis. Although the K-means clustering algorithm has its limitations, it is considered a well-established clustering algorithm that has been widely applied in various fields such as stock analysis and geographic information services. By utilizing this algorithm, online English learners with similar learning behaviors and characteristics can be grouped together to achieve homogeneity within the group and heterogeneity among different groups. Specifically, characteristics of online English learners and their corresponding learning process data are integrated through student numbering. The K-means algorithm is then applied to perform clustering after normalizing all data variables. Group behavior data are obtained by integrating the learning process data of online English learners in the same group based on the clustering results. The specific pathway flow is shown in Figure 1.

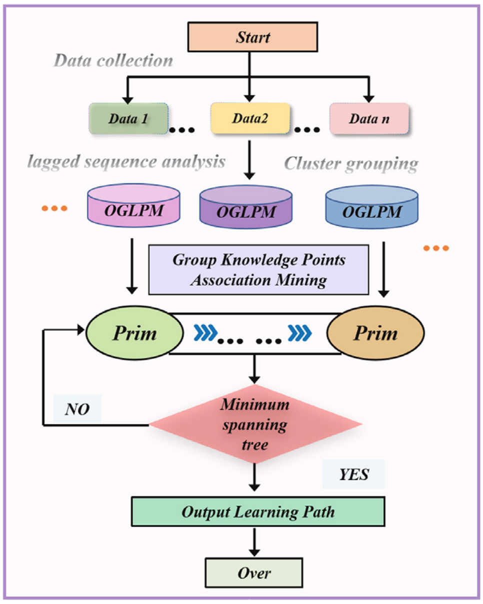

Fig. 1. Online group learning path construction strategy flow

Using LSA to analyze the group behavior data, which includes information on online English learners, learning behaviors, and learning time, enables the extraction of a series of learning behavior sequences of online English learners in the group in chronological order. Based on processing and coding the group behavioral data, it is imported into the lagged sequence analysis tool to calculate the frequency table of the behavioral sequences and the adjusted residual values. This process helps obtain the frequency and probability values of the behavioral sequences of the online English learners in the group. First, the K-means algorithm is used to cluster and group the online English learners. Since the learning process data and the characteristics of online English learners use different scales, it is necessary to normalize all the attributes based on the integration of the two datasets. The profile coefficients for various classification quantities are presented in Table 1.

Table 1. Table of LSA profile coefficients for different numbers of classifications

K	2	3	4	5	6
SC	0.304	0.259	0.239	0.182	0.238

Secondly, the learning behavior data of online English learners is integrated based on their grouping. The frequency of learning behavior sequences generated by learners in each group is then counted using the lag sequence analysis tool. This process results in the behavior sequence frequency matrix presented in Tables 2 and 3. The matrix counts the frequency of transitions between behavior sequences and specifies the number of transitions before and after behaviors in the learning log data. The number of jumps. The rows in the table represent the preceding behaviors, while the columns represent the subsequent behaviors following the occurrence of the corresponding preceding behaviors. The transitions from the preceding behaviors to the following behaviors form the behavioral sequences, and the data in the table indicate the frequency of these learning behavioral sequences. For example, the number "2196" in row 1 and column 2 of Table 3 indicates the frequency of the behavior sequence CA, i.e., the number of times that the lesson (C) behavior is followed by the homework practice (A) behavior.

Table 2. LSA Group 1 behavioral sequence frequency matrix

n	C	A	F	Q	P	R
C	296	219	8	8	4	3
A	180	402	110	230	49	6
F	415	659	581	31	5	2
Q	3	259	0	984	0	2
P	0	55	1	0	63	5
R	4	10	1	0	4	13

Table 3. LSA Group 2 behavioral sequence frequency matrix

n	C	A	F	Q	P	R
C	3201	2296	7	18	3	16
A	1770	436	1274	329	43	7
F	563	648	829	51	9	3
Q	9	380	1	50	1	1
P	1997	4	4	1	80	7
R	3	30	0	2	2	12

The frequency matrix was then analyzed using lagged sequence analysis, and the behavioral sequence residuals obtained are shown in Tables 4 and 5. The data in the tables represent the residual values of behavioral sequences (Z-score), and Z-score > 1.96 indicates that the frequency of the corresponding behavioral sequences is significant. The frequency of occurrence of the behavioral sequences indicated by the bolded data in the two tables reached a significant level. It can be observed that there are fewer significant behavioral sequences related to taking the test (Q), more significant behavioral sequences composed of the same behaviors, and a difference in the probability of the occurrence of behavioral sequences that involve bi-directional jumps. The significant residual values are normalized, and the resulting values indicate the probability of occurrence of the corresponding behavioral sequences.

Table 4. LSA Group 1 behaviorally adjusted residuals

n	C	A	F	Q	P	R
C	26.08	25.56	–38.75	–32.44	–9.16	–3.82
A	9.31	–29.71	33.84	–9.72	2.18	–1.33
F	–17.15	8.48	25.39	–12.62	–3.3	–1.25
Q	–32.69	–7.66	–15.26	83	–3.85	–0.74
P	–9.85	3.46	–4.32	–3.85	54.57	8.27
R	–3.56	0.13	–1.81	–1.95	6.35	44.8

Table 5. LSA Group 2 behaviorally adjusted residuals

n	C	A	F	Q	P	R
C	35.98	30.43	–39.8	–42.46	–9.09	–0.96
A	9.68	–26.13	36.8	–16.48	0.83	–2.06
F	–12.83	3.97	34.02	–19.31	–2.86	–1.73
Q	–42.88	–13.74	–22.59	4.85	–4.5	–1.65
P	–9.41	2.26	–4.76	–5.16	67.0	79.4
R	–4.77	5.35	–2.94	–2.41	2.17	28.75

To simplify the data on significant behavioral sequences, behavioral sequence conversion diagrams were created for different learning groups using the adjusted residual values, as depicted in Figures 2 and 3. The nodes in the figure represent learning behaviors with a significant frequency of occurrence of behavioral sequences, which can be determined from the adjusted residual value table. Arrows connect these significant behavioral sequences, with the arrow direction indicating the conversion direction of the significant learning behavioral sequences. Arrows labeled with numbers indicate the probability of conversion of the behavioral sequences. Figure 2 illustrates the behavioral sequence transformation diagram of Group 1. It is evident that the behavioral sequence of online English learners in Group 1 is relatively straightforward, following a linear trend. The potential behavioral sequences include viewing the course, practicing homework, browsing the page content, and checking resources (C→A→P→R).

After reviewing the course syllabus, learners in this group typically engage in direct homework practice to identify their weaknesses and then utilize related resources for learning. The online English learners in the group tended to repeat the discussion, resources, and quiz. The quiz module was relatively independent, and the learners had a higher probability of retaking the quiz (Q–Q) and concluding the study upon reaching the learning goal without engaging in any further behaviors. There is a close connection between behaviors, and the reverse behavioral sequence, which consists of significant behavioral sequences, also has a high probability of occurring. The likelihood of the same behavioral patterns is higher. For instance, learners will practice their homework after studying the related resources. If the practice is unsuccessful, they will revisit the related resources, indicating that online English language learners in the group possess a strong ability for retrospective learning. They are skilled at continuously summarizing and reflecting during the learning process.

Figure 3 illustrates the behavioral sequence transformation diagram for Group 2. It is evident that Group 2 online English learners have well-defined learning objectives, with homework practice behavior being central. There is a strong interaction between the homework module and other modules. The potential behavioral sequences include checking the course, homework practice (C–A), browsing the page content, homework practice (P–A), checking the resources, homework practice (R–A), homework practice, and participating in discussions (A–F). Learners in this group typically engage in homework practice after engaging in activities such as viewing the course, browsing page content, and checking resources. They enhance their practice through communication and discussion. The probability of the occurrence of a behavioral sequence consisting of repeated behaviors is higher than that of engaging in homework practice for online English learners, similar to the behavioral sequence transformation diagram of Group 1. Online English learners tend to participate in discussions repeatedly, access learning resources multiple times, and retake quizzes. The quiz module is relatively independent, and learners in online English groups are more likely to retake quizzes (Q) before concluding the learning process upon achieving the set learning objectives, with no further behaviors observed thereafter. No other behaviors occurred afterward. In addition, the likelihood of the reverse behavior sequence, which includes significant behavior sequences, is relatively low. This mainly occurs between checking the course-homework practice, browsing the page content—checking resources, and participating in the discussion for homework practice. This indicates that online English learners in Group 2 are willing to switch between different types of resources, repeatedly check the course syllabus for homework practice, and are also willing to reflect and summarize through discussion and exchange to enhance their practice level.

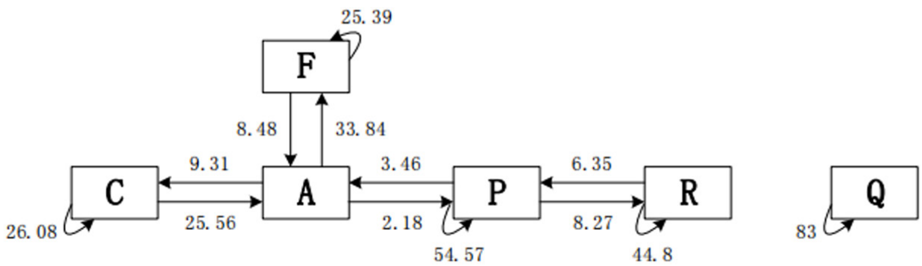

Fig. 2. Behavioral sequence transformation diagram for Group 1

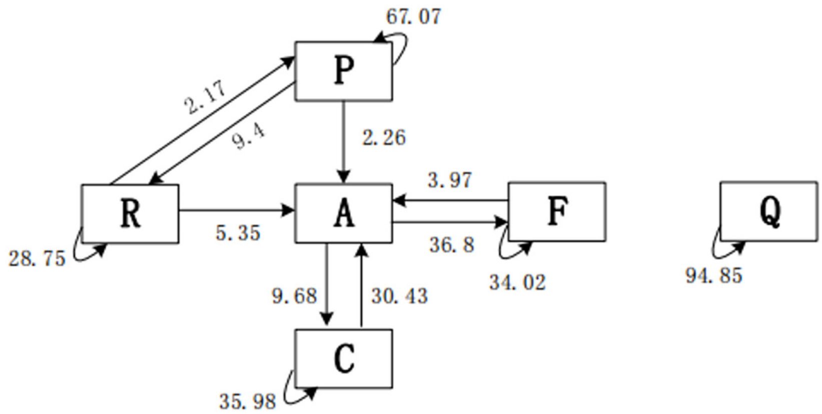

Fig. 3. Behavioral sequence transformation diagram for Group 2

Based on the mapping relationship between learning behaviors, learning activities, and knowledge points, data mining techniques are used to extract the interconnections among knowledge points and visualize them. Figure 4 represents the knowledge point association graphs of Group 1 and Group 2, where nodes symbolize knowledge points and connected edges depict the associations between them. It can be seen that each knowledge point has multiple edges connected to it, indicating that there are various associations between knowledge points. In addition, there are differences in the associations between knowledge points identified by various learning groups.

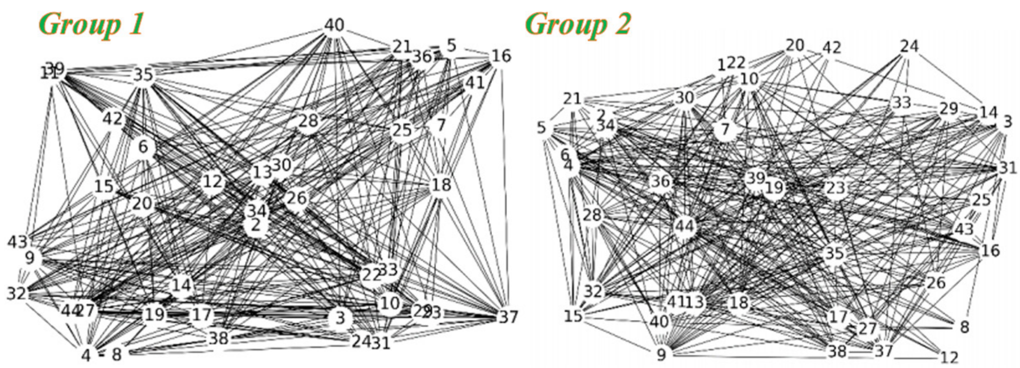

Fig. 4. Group knowledge points correlation chart

Table 6 shows the final results of each algorithm for constructing learning paths. The numbers indicate the number of knowledge points, the arrows point to the next knowledge point to be learned, and the last row in the table represents the teacher's preset course learning path. Comparing the predefined group learning paths, it can be observed that the group learning paths produced by the Prim algorithm and the topological sorting algorithm differ significantly from the predefined paths. This suggests that OGLPM-S can efficiently extract various connections among knowledge points and create unique group learning paths. Comparing the inter-group learning paths, the learning paths of Group 1 and Group 2 constructed using the same algorithm are quite different. This indicates that the OGLPM-S clustering grouping is effective, and the algorithm can generate diverse group learning paths based on the characteristics of online English learners in each group.

Table 6. LSA learning group paths generated by different algorithms

Arithmetic	Clusters	Learning Path
Prim	Group 1	1→2→7→3→5→8→12→10→4→9→15→18→13→23→29→28→30→36→14→16→17→19→6→20→11→21→22→34→27→31→24→25→26→32→37→33→35→39→38→40→44→41→42→43
	Group 2	1→10→3→4→6→9→2→7→5→8→11→12→14→16→20→21→22→15→13→19→18→17→23→29→28→24→30→26→27→31→25→41→34→32→35→33→43→42→37→38→39→40→44→36
Topological Ordering (T.O.)	Group 1	1→2→7→3→5→8→12→10→4→9→15→18→13→23→29→28→30→36→14→16→17→19→6→20→11→21→22→34→27→31→24→25→26→32→37→33→35→39→38→40→44→41→42→43
	Group 2	1→10→3→4→6→9→2→7→5→8→11→12→14→16→20→21→22→15→13→19→18→17→23→29→28→24→30→26→27→31→25→41→34→32→35→33→43→42→37→38→39→40→44→36
Predefined learning paths	/	1→2→3→4→5–6→7→8→9→10→11→12→13→14→15–16–17→18→19→20→21→22→23→24→25→26→27→28→29→30→31→32→33→34→35→36→37→38→39→40→41→42→43→44

To better analyze the differences between the group learning paths, the group learning paths constructed by each algorithm are visualized using a line graph, as shown in Figure 5. In the graph, the horizontal axis represents the sequence in which knowledge points are learned, while the vertical axis represents the value of the knowledge points to be learned. From the distribution of knowledge points in group learning paths, the learning paths of Groups 1 and 2 are shown in Figure 5. In this study, we observed that there were fewer instances of the same knowledge points among groups following the same learning sequence, and the learning trajectories of different groups using the same algorithm exhibited lower levels of similarity. In the clustering process of the K-means algorithm, the behavioral characteristics and implicit traits of online English learners are considered. The impact of intra-group homogeneity and inter-group heterogeneity becomes more pronounced after grouping. The inter-group knowledge point associations identified through the process are also distinct. Consequently, the variations in learning paths among groups formed by the same algorithm are evident, further confirming the validity of the clustering grouping of the OGLPM-S. The learning paths of the two groups in Figure 5 show an overall upward trend. The two groups of learning path trends are more random. The reason for the difference is that in the construction process, the Prim algorithm can generate the smallest tree of knowledge points based on the adjusted association value of the knowledge points, ensuring the maximum correlation between the knowledge points based on the logical structure of the knowledge points. On the other hand, the topological sorting algorithm doesn't take into account the association value of the knowledge points. It only sorts from the forward and backward pointing relationship of the knowledge points, which generates a greater conflict between the path and the original logical structure of the knowledge points, leading to an overall fluctuation of the path and the knowledge points. The logical structure has a significant conflict, and there is considerable fluctuation overall.

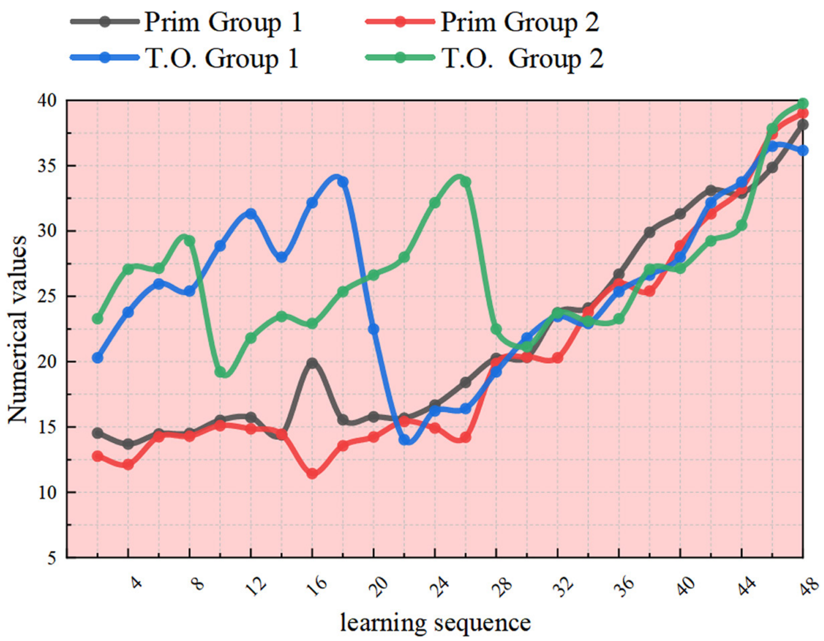

Fig. 5. Comparison of group learning paths

As shown in Table 7, when the group size is 2, the correlation between the group learning paths constructed by the Prim algorithm and the topological sorting algorithm is 8.832 and 8.7774, respectively. The correlations are 0.577 and 0.241, indicating that the learning paths constructed by the topological sorting algorithm have a small correlation and do not align with the learning characteristics of the online English learners in the group. In contrast, the correlation between the two learning paths constructed by the Prim algorithm is higher. This demonstrates that the method proposed in this paper is more effective. It can not only generate various learning paths based on group characteristics but also guarantee that the constructed group learning paths have a high correlation.

Table 7. LSA group learning path correlations

Algorithm/Grouping	Group 1	Group 2
Prim	8.332	8.777
topological ordering	0.577	0.241

3 INITIAL REALIZATION OF A PLATFORM FOR BUILDING LEARNING PATHS

With the development of network technology, learning platforms can integrate multidimensional data, and online learning-based platforms have become an inevitable trend. In this paper, the core computing system of the intelligent learning platform mentioned above is constructed in the preceding chapter. Based on this, the overall construction and expansion of visualization are carried out, and the overall architecture of intelligent interaction for online English learning is shown in Figure 6. The platform was entirely developed in Java. The front-end utilizes HTML and jQuery technologies to customize the video player. The back-end follows the classic three-tier architecture, consisting of the Web layer, business layer, and persistence layer. In this architecture, the Web layer transfers data from the front-end to the business layer. The business layer interacts with the persistence layer, which in turn communicates with the database through logic processing.

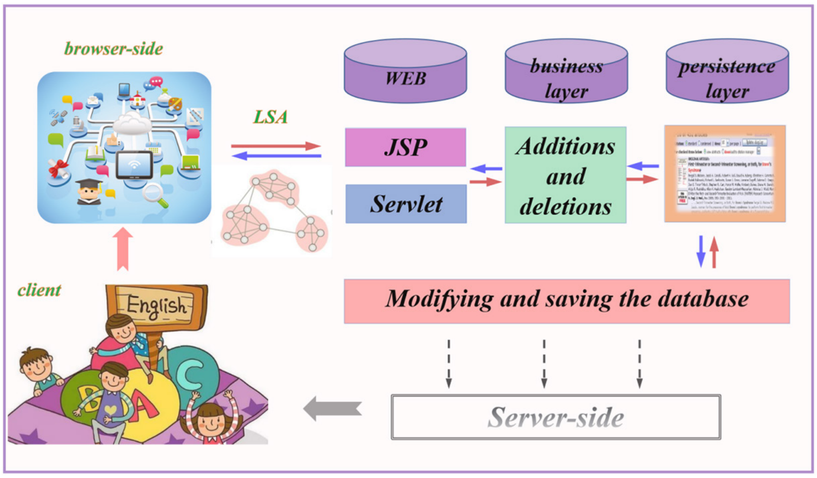

Fig. 6. Comparison of group learning paths

In the platform shown in Figure 6, personal information of online English learners, behavioral records, and time records are stored using the LSA method. Teachers can upload and modify courseware, edit attributes, view records, and perform other operations. Online English learners can study the course, bookmark it, practice the exercises, and discuss the specific learning process with other students. Exercises with a high error rate and frequently discussed knowledge points will be collected by the database and eventually displayed in the popular section. Teachers can establish course requirements and assign knowledge labels. Based on the behavior of online English learners and teachers, data on online English learners and knowledge points can be collected. Online English learners can be grouped using a group learning path construction engine. Subsequently, group behavior can be analyzed using lagged sequence analysis. The association between group knowledge points can be identified based on this analysis. Finally, group learning path recommendations can be generated using the minimum spanning tree Prim algorithm and then recommended to online English learners. English learners. Among them. Based on the learning log to retrieve the behavioral data of online English learners, the data contains attributes such as online English learner ID, type of learning behavior, and time of behavior. This data is transformed into a two-dimensional matrix and analyzed using the K-means clustering algorithm for clustering analysis of online English learners. Subsequently, based on the grouping information, the behavioral data of online English learners is integrated. Intergroup data containing attributes such as learning behavior and time of behavior are stored and analyzed. The intergroup data containing learning behavior, behavior occurrence time, and other attributes is stored in the database. The group learning behavior data is coded using letters. Specific learning behavior types are converted into coding symbols recognizable by lag sequence analysis. The behaviors are then arranged based on the time of the online English learner ID and the time of the learning behavior. This process results in a set of coded behavioral data organized systematically. The coded behavioral data are imported into the lag sequence analysis tool through an external interface, and after the analysis is completed, the probability of occurrence between different behavioral sequences is judged, and the residual values of the significantly occurring behavioral sequences are stored in the database. The LSA-OGLPM-S strategy proposed by the above idea can successfully construct a group learning path based on the behavioral data of online English learners, which is suitable for online English learners to carry out online learning.

4 CONCLUSIONS

Here, an efficient model for online group learning paths based on LSA with a blended learning perspective is devised. The model incorporates techniques such as the lagged sequence analysis method, data mining method, and minimum spanning tree algorithm to propose the OGLPM-S strategy. The experimental results demonstrate that the strategy is feasible, efficient, and stable. Among them, when comparing the inter-group learning paths, the learning paths of Groups 1 and 2 constructed using the same algorithm are significantly different. This suggests that the OGLPM-S clustering grouping is effective, and the algorithm can generate diverse group learning paths tailored to the characteristics of online English learners in each group. The online intelligent learning platform is designed for providing group learning path construction services. The paper describes the overall architecture, functional process, strategy implementation, and construction results of the platform. It demonstrates that the OGLPM-S strategy proposed in this paper can successfully create group learning paths based on the behavioral data of secondary school students. This approach is suitable for online English learners engaging in online learning. In summary, research on online group learning paths combined with LSA behavior analysis, data mining, and other personalized service technologies can effectively utilize potential information to provide personalized online services to English learners. This, in turn, can enhance the online learning experience and effectiveness of English learners.

5 REFERENCES

[1] X. Yang, "Connotation and characteristics of wisdom education in the information age," *China Electrified Education*, vol. 1, pp. 29–34, 2014.

[2] L. Chen, "Research on the construction of three-dimensional learning resources for higher education courses – the perspective of promoting the transformation of learning styles," *China Electrified Education*, vol. 11, pp. 95–97, 2013.

[3] X. Li and D. Ma, "Problems and their countermeasures in the construction of university video open courses in China," *Modern Education Technology*, vol. 7, pp. 11–16, 2012.

[4] G. Siemens and P. Long, "Penetrating the fog: Analytics in learning and education," *Educause Review*, vol. 46, no. 5, pp. 30–32, 2011.

[5] T. Mckay, K. Miller, and J. Tritz, "What to do with actionable intelligence: E 2Coach as an intervention engine," in *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, NewYork: ACM, 2012, pp. 88–91.

[6] S. Wei, "Learning analytics from the perspective of online education administrators—construction and application of online teaching performance assessment model," *Modern Education Technology*, vol. 24, no. 9, pp. 79–85, 2014.

[7] Z. Papamitsiou and A. A. Economides, "Learning analytics, and educational data mining in practice: a systematic literature review of empirical evidence," *Educational Technology & Society*, vol. 17, no. 4, pp. 49–64, 2014.

[8] C. N. Gunawardena, C. A. Lowe, and T. Anderson, "Analysis of global online debate and the development of an interaction analysis model for examining social construction of knowledge in computer conferencing," *Journal of Educational Computing Research*, vol. 17, no. 4, pp. 397–431, 1997. https://doi.org/10.2190/7MQV-X9UJ-C7Q3-NRAG

[9] B. S. Bloom, *Taxonomy of Educational Objectives*. New York: McKay, 1956.

[10] Y.-T. Sung, H.-T. Hou, C.-K. Liu, and K.-E. Chang, "Mobile guide system using problem-solving strategy for museum learning: A sequential learning behavioral pattern analysis," *Journal of Computer Assisted Learning*, vol. 26, no. 2, pp. 106–115, 2010. https://doi.org/10.1111/j.1365-2729.2010.00345.x

[11] C. L. Lai and G. J. Hwang, "A spreadsheet-based visualized Mindtool for improving students' learning performance in identifying relationships between numerical variables," *Interactive Learning Environments*, vol. 23, no. 2, pp. 230–249, 2015. https://doi.org/10.1080/10494820.2014.997247

[12] A. C. Jeong, "The sequential analysis of group interaction and critical thinking in online," *The American Journal of Distance Education*, vol. 17, no. 1, pp. 25–43, 2003. https://doi.org/10.1207/S15389286AJDE1701_3

[13] H. T. Hou, "Exploring the behavioral patterns of learners in an educational massively multiple online role-playing game (MMORPG)," *Computers & Education*, vol. 58, no. 4, pp. 1225–1233, 2012. https://doi.org/10.1016/j.compedu.2011.11.015

[14] E. Eryilmaz, J. van der Pol, T. Ryan, P. M. Clark, and J. Mary, "Enhancing student knowledge acquisition from online learning conversations," *International Journal of Computer-Supported Collaborative Learning*, vol. 8, no. 1, pp. 113–144, 2013. https://doi.org/10.1007/s11412-012-9163-y

[15] X. M. Yang, J. H. Li, X. S. Guo, and X. Li, "Group interactive network and behavioral patterns in online English-to-Chinese cooperative translation activity," *The Internet and Higher Education*, vol. 25, pp. 28–36, 2015. https://doi.org/10.1016/j.iheduc.2014.12.003

[16] F.-J. Liu and B.-J. Shih, "Learning activity-based e-learning material recommendation system," in *Proceedings of the Ninth IEEE International Symposium on Multimedia Workshops (ISMW2007)*, 2007, pp. 343–348. https://doi.org/10.1109/ISM.Workshops.2007.64

[17] Y. Zha and Q. Zhu, "Research on vocational student personalized learning recommended model," in *Proceedings of the International Conference on Education Management and Information Technology*, 2015, pp. 800–805. https://doi.org/10.2991/icemit-15.2015.166

[18] J.-C. Zhao, L. Chen, and J. X. Guo, "A recommendation algorithm based on collaborative filtering technology in distance learning," in *Proceedings of the 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2017, pp. 2320–2323. https://doi.org/10.1109/IAEAC.2017.8054435

[19] H. Li, F. Du, M. Zhang, L. Wang, and X. Yu, "Research on collaborative filtering recommendation of learning resource based on knowledge association," in *Proceedings of the International Conference on Innovative Technologies and Learning*, 2018, vol. 11003, pp. 561–567. https://doi.org/10.1007/978-3-319-99737-7_59

[20] Y. Wang *et al.*, "Research on personalized recommendation of learning resources based on collaborative filtering technology," *Journal of Distance Education*, vol. 29, no. 3, pp. 66–71, 2011.

[21] W. Wang, "Research on collaborative filtering based autonomous learning system in secondary schools," Dalian Maritime University, 2017.

[22] C. Qiang *et al.*, "Personalized resource recommendation based on tagging and collaborative filtering," *Computer Science*, vol. 41, no. 1, pp. 69–71, 2014.

[23] C.-M. Chen, "Intelligent web-based leaming system with personalized leaming path guidance," *Computers & Education*, vol. 51, no. 2, pp. 787–814, 2008. https://doi.org/10.1016/j.compedu.2007.08.004

[24] X.-H. Tan, R.-M. Shen, and Y. Wang, "Personalized course generation and evolution based on genetic algorithms," *Journal of Zhejiang University. Science C, Computers & Electronics*, vol. 13, no. 12, pp. 909–917, 2012. https://doi.org/10.1631/jzus.C1200174

[25] J.-W. Li, Y.-C. Chang, C.-P. Chu, and C.-C. Tsai, "A self-adjusting e-course generation process for personalized learning," *Expert Systems with Applications*, vol. 39, no. 3, pp. 3223–3232, 2012. https://doi.org/10.1016/j.eswa.2011.09.009

[26] T.-Y. Chang and Y.-R. Ke, "A personalized e-course composition based on a genetic algorithm with forcing legality in an adaptive learning system," *Journal of Network and Computer Applications*, vol. 36, no. 1, pp. 533–542, 2013. https://doi.org/10.1016/j.jnca.2012.04.002

[27] W. Han, "Personalized course evolutionary based on genetic algorithm," *International Journal of Multimedia and Ubiquitous Engineering*, vol. 9, no. 11, pp. 255–264, 2014. https://doi.org/10.14257/ijmue.2014.9.11.25

[28] Y.-S. Lin, Y.-C. Chang, and C.-P. Chu, "An innovative approach to scheme learning map considering tradeoff multiple objectives," *Technology & Society*, vol. 19, no. 1, pp. 142–157, 2016.

[29] P. Dwivedi, V. Kant, and K. K. Bharadwaj, "Learning path recommendation based on modified variable length genetic algorithm," *Education and Information Technologies*, vol. 23, pp. 819–836, 2018. https://doi.org/10.1007/s10639-017-9637-7

[30] Y. J. Yang and C. Wu, "An attribute-based ant colony system for adaptive learning object recommendation," *Expert Systems with Applications*, vol. 36, no. 2, pp. 3034–3047, 2009. https://doi.org/10.1016/j.eswa.2008.01.066

[31] C.-C. Hsu, H.-C. Chen, K.-K. Huang, and Y.-M. Huang, "A personalized auxiliary material recommendation system based on the leaming style on Facebook applying an artificial bee colony algorithm," *Computers & Mathematics with Applications*, vol. 64, no. 5, pp. 1506–1513, 2012. https://doi.org/10.1016/j.camwa.2012.03.098

[32] R. Sharma, H. Banati, and P. Bedi, "Adaptive content sequencing for e-leaming courses using ant colony optimization," in *Proceedings of the Proceedings of the International Conference on Soft Computing for Problem Solving (SocProS 2011), 2011. Advances in Intelligent and Soft Computing (AINSC)*, 2012, vol. 131, pp. 20–22. https://doi.org/10.1007/978-81-322-0491-6_53

[33] E. Kurilovas, I. Zilinskiene, and V. Dagiene, "Recommending suitable leaming scenarios according to learners' preferences: An improved swarm-based approach," *Computers in Human Behavior*, vol. 30, pp. 550–557, 2014. https://doi.org/10.1016/j.chb.2013.06.036

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