Visual Analysis of the Time Management of Learning Multiple Courses in Online Learning Environment

Huan He [1,2] * Bo Dong [3,4] † Qinghua Zheng [1,2] ‡ Dehai Di [5] § Yating Lin [1,2] ¶

[1] Shaanxi Province Key Laboratory of Satellite and Terrestrial Network Tech. R&D, Xi'an Jiaotong University
[2] School of Electronic and Information Engineering, Xi'an Jiaotong University
[3] School of Continuing Education, Xi'an Jiaotong University
[4] National Engineering Lab for Big Data Analytics, Xi'an Jiaotong University
[5] School of Management, Xi'an Jiaotong University

ABSTRACT

Self-paced online learning not only provides the opportunities of learning anytime but also chanllenges students' time management, especially in the context of learning multiple courses at same time. The inappropriate scheduling of multiple courses may affect student engagement and learning performance, thus how to arrange the study time of multiple courses is a concern of both instructors and students. Existing studies related to student engagement and time management in online learning mainly focus on providing self-regulated learning strategies and evaluating learning performance. However, these methods have limited abilities to gain intuitive understanding of the time management of multi-course learning. To address this issue, we present LearnerVis to help users analyze how students schedule their multi-course learning. LearnerVis visualize the temporal features of learning process, and it enables users to customize student groups to compare the differences in student engagement and time management. A case study is conducted to demonstrate the usefulness of the system with real-word dataset.

Index Terms: Human-centered computing—Visualization—Visual analytics; Applied computing—E-learning

1 INTRODUCTION

Acquiring new knowledge and skills always takes a lot of time to learn, and there is no exception in online learning environment. With the advantages of learning anywhere and anytime, students can schedule their online learning at their own pace. However, this self-scheduled learning process also challenges students' time management, especially when learning multiple courses at the same time (e.g., specialized courses and online undergraduate programs) [2, 17]. In the less supervised online learning environment, the inappropriate scheduling of multi-course study time may reduce student engagement, course completion rate and course rating [2,22]. Therefore, understanding the time management of learning multiple courses has been an important issue for both instructors and students.

With the support of learning management system (LMS), students' online learning process can be recorded as log data, which is a potential data source for analyzing student engagement and their time management. Existing studies have proposed many indicators based on log data to measure the time management feature, such as the time that students spent on certain tasks [6, 13], the interval time between two tasks [2] and the remaining time before the deadlines [11] etc. By using these indicators, recent studies have examined self-regulated learning strategies [14, 15], learners' behaviors [21], and influences of time management on learning performance [22].

However, due to the complexity of learning multiple courses, existing indicators and methods have difficulties in characterizing and visualizing the temporal features of long-term learning process. To address this issue, we introduce the LearnerVis system for instructors to analyze students' time management patterns intuitively. First, we propose an engagement calendar matrix to represent daily learning activities based on well-studied indicators. Then, we develop a visual analytics system with five coordinated views to explore the temporal patterns of multi-course learning process. Main contributions of this work are summarized as follows:

1) An engagement calendar matrix model for describing and analyzing the time management in online learning process, which not only captures the temporal aspect of learning activities, but also supports visual understanding.

2) An interactive visual analytics system for exploring the time management of multi-course learning based on the proposed model.

2 RELATED WORK

2.1 Student Engagement and Time Management

Scholars have typically identified student engagement as a construct that consists of three components: behavioral engagement, emotional engagement, and cognitive engagement [10]. In this work, we focus on students' behavioral engagement and throughout this paper, "engagement" will refer to "behavioral engagement". To measure student engagement and time management features in online learning environments, many indicators have been proposed from various perspectives. The most commonly used indicators are based on the time spent on interactions with functions and resources in the LMS. For instance, Guo et al. [9] used the time that a student spends on a video as proxies for student engagement. Van der Sluis et al. [19] used the dwelling time (how much time students spend watching a video) and the dwelling rate (how much of the video they watch) to measure student engagement with educational videos. Bote-Lorenzo and Gómez-Sánchez [1] defined 16 indicators for measuring student engagement in each chapter of an online course, such as the percentage of lecture videos that were totally or partially watched.

However, these indicators compressed the details of time management into a few values, thus caused the loss of temporal and sequential information in learning process. Our work extends these studies by dividing day segments to preserve the detailed temporal information in student engagement over time.

2.2 Online Learning Visualization

Previous studies applied statistical tools and machine learning methods to the analysis of student engagement and time management. However, the findings are usually presented in tables and basic charts, which are difficult to provide intuitive impression and help users conduct further interactive analysis. To address this issue, an

*e-mail: hehuan@mail.xjtu.edu.cn
†e-mail: dong.bo@mail.xjtu.edu.cn
‡e-mail: qhzheng@mail.xjtu.edu.cn
§e-mail: ddh@mail.xjtu.edu.cn
¶e-mail: linyating@stu.xjtu.edu.cn

emerging trend is applying visualization techniques to present the data and help users analyze the patterns of online learning. For instance, Xia and Wilson [20] developed a comparative heatmap tool that enabled instructors to explore and compare student's video engagement. Shi et al. [18] developed VisMOOC system to show the temporal patterns of viewing activities in clickstream data with stacked graphs and calendar heatmap. Chen et al. [3] developed a visual analytics system called PeakVizor to investigate viewing patterns in clickstream data. Fu et al. [7] developed VisForum system to analyze the temporal information of user groups. Chen et al. [4] developed ViSeq system to capture the sequential information in online learning activities.

These works apply a variety of visualization and interactive techniques in online learning, such as thread river [8] and calendar heatmap [18] to show the temporal features of learning process, which inspire the design of our system.

3 TASK ANALYSIS

With respects of user needs for analyzing students' time management of learning multiple courses, we conducted several rounds of interviews with four domain experts from our distance education school. Two of them are senior engineers of technology center and the other two are course instructors. The task requirements are summarized as follows:

T.1 How do students schedule learning in a period of time? In the long-term online learning process, a variety of factors affect students' learning time, which may lead to changes in the learning schedule. This kind of feature is important for understanding students' actual time management.

T.2 How do students arrange the study of multiple courses? Since there is no fixed curriculum like the traditional classroom, students have to arrange the progress of each course on their own pace. Understanding the arrangement of multi-course learning will help provide instructions.

T.3 What is the relationship between student engagement and time management? The student's time management is related to the time spent on learning, which may directly affect student engagement. Studying this relationship helps to understand the changes in student engagement, and provide basis of instructional interventions.

3.1 Design Rationale

Based on the tasks addressed above, we derive the following design rationales to guide our design.

R.1 Presentation of student engagement: In the long-term learning process, there may be a correlation between time management and student engagement (T.1, T.3). We need to present the changes in student engagement over time.

R.2 Exploration of multi-course time management: The learning progress of multiple courses may overlap in a period of time, which in turn reflects how students arrange multiple courses (T.2). Visualization should demonstrate the multi-course time management.

R.3 Exploration among different student groups: Analyzing the differences of various student groups helps to understand the relationship between time management and student engagement (T.2, T.3). Visualization should support comparison among different student groups.

R.4 Interactive exploration: Since students, student groups and their engagement indicators are related to each other, it is necessary to provide an interactive interface that allow users to customize student groups for exploration.

4 DATA ABSTRACTION

To capture the time management features of multi-course learning, we propose the engagement calendar matrix to model the long-

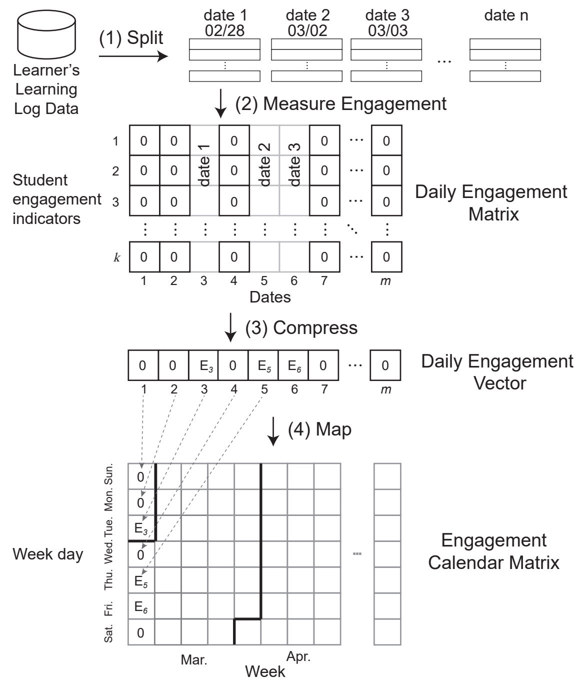

Figure 1: The engagement calendar matrix.

term learning process. As shown in Fig. 1, there are four steps to produce the engagement calendar matrix of each student. 1) We split the time-stamped learner-generated learning log data into separate segments on a daily basis. 2) The daily student engagement is measured by k indicators, such as the interaction counts of student-course, student-student and student-system, video viewing time, session time [6, 12, 17] etc. We embed the daily student engagement into a $k \times m$-dimensional daily engagement matrix in date order, where m is the number of days. 3) The daily engagement matrix is compressed into the $1 \times m$-dimensional daily engagement vector. 4) We map each element of the compressed vector in the calendar-like $7 \times w$-dimensional engagement calendar matrix by date, where w represents the number of weeks.

The engagement calendar matrix can reflect various aspects of the student engagement over time according to the way of compressing daily engagement matrix in the third step. For example, weighted linear aggregation of all indicators can represent the overall engagement, and selecting single indicator can represent a particular aspect of engagement. In this paper, we use a weighted sum of all indicators to generate the thumbnails of learning calendar. In addition, we also select the video related indicators (i.e., video utilization rate, the ratio of time spent on viewing to the video duration) to represent daily learning activities according to suggestions from domain experts.

To capture the time management characteristics and predict student's grade point in the final exam, we design a prediction model based on convolutional neural network to extract the temporal features of the engagement calendar matrix. This prediction model consists of two convolutional layers to capture the short-term (i.e., 1×7 column-wise) and long-term (i.e., $n \times 1$ row-wise) patterns of engagement. We use the prediction results to help users analyze the impact of time management on student's exam performance.

5 VISUAL DESIGN

5.1 Learner Overview

To provide users with intuitive impression on the overall engagement distribution of all students (R.1), we use scatter chart to show the statistics on the indicators of student engagement (Fig. 2(b)). In

Figure 2: Demonstrating the LearnerVis system that shows: (a) a group list containing customized student groups; (b) a Learner Overview depicting the overall engagement distribution of all students in scatter charts; (c) a Comparison View showing engagement differences between student groups; (d) a Learning Calendar View showing the overall learning process of each student in the selected groups in group list; and (e) a Learning Details View revealing the time management of multi-course learning process.

this chart, each gray dot represents a student, while other colored dots represent students who belongs to a specific student group. The x-axis and the y-axis can be set to any indicator to see different engagement distribution of same population. For example, as shown in Fig. 2(b1), the x-axis "Student-LMS Count" represents the total number of non-learning interactions with the LMS system, such as sign in/off and browse news. The y-axis "Student-Content Count" represents the total number of interactions with course resources, such as course videos, lecture notes, textbooks and assignments. In addition, users can preview the engagement distribution of other indicators in a set of scatter chart thumbnails (Fig. 2(b2)).

In this view, we use FIt-SNE algorithm [16] to map the high-dimensional student engagement to a 2D plane for discovering potential clusters. We also design an automatic group creation tool based on DBSCAN algorithm [5] to cluster dots based on the dot density. Users can also select students of interest (Fig. 2(b3)) with an interactive selector for further comparison (R.4).

5.2 Comparison View

To understand the engagement difference among student groups (R.3), we use a set of box charts to compare the student groups across multiple indicators. As shown in Fig. 2(c), each box chart displays an indicator from left to right, and each series represents a student group from top to bottom. The color of each series is consistent with the color displayed in the group list (Fig. 2(a)).

5.3 Learning Calendar View

We design this view to understand the temporal information of overall learning process (R.1 and R.2). In this view, the engagement calendar matrix defined in Section 3 is color-encoded to show the whole learning process (Fig. 2(d)). This view displays student groups in rows from top to bottom, in which the engagement calendar matrix of each student is shown from left to right. When mouse is over each engagement calendar matrix, the corresponding dot in the Learner Overview will be enlarged.

5.4 Learning Details View

In this view, two panels are designed to show the time management of multi-course learning (R.3), namely Daily Viewing Panel and Weekly Statistics Panel. To distinguish learning behaviors among courses, we encode each course with a color, and the course color encoding used in this view is independent of other views (Fig. 2(e)).

Daily Viewing Panel: In this panel, we design a calendar-based chart to visualize the daily video utilization of each course, which shows a student's viewing history. The date range of this chart is consistent with the thumbnail in Learning Calendar View. In each date cell, a check-in icon in the upper-right corner indicates that the student has logged in the LMS on that day. Meanwhile, all the videos viewed on that day are listed as video cells, which are color-encoded by the course color.

Each video cell represents a courseware video, and the video utilization rate is mapped to the width of the inner block. For example, a full filled video cell represents this video has been completely viewed, while a half filled video cell represents only half of the video has been viewed. When users click the date cell, detailed viewing list will be shown in a popup window (R.4). In addition, the course exam dates are marked in the upper right corner of the corresponding date cell.

Weekly Statistics Panel: During the evaluation of early prototype system, domain experts comment that the daily viewing panel fully demonstrates the details but lacks understanding of the overall feature of learning multiple courses. Therefore, we design this panel, which shows a stacked bar chart to illustrate the weekly viewing statistics (Fig. 2(e2)). The x-axis of this chart represents the weeks, where each bin corresponds to the week column in the above Daily Viewing Panel (e.g., as shown in Fig. 2(e3), the bin of week 5 corresponds to the week from March 26 to April 1). Each bar of this chart represents the total number of viewed videos of each course in corresponding week. The color encoding used in this chart is corresponding to the Daily Viewing Panel.

6 Case Study

To verify the usability of LearnerVis, we conduct case study with two domain experts from our online education school (EA and EB). Both of them are course instructors and have experience in teaching programming foundation courses of computer science. The learning log data used in case study is from our online education school's online undergraduate program, which consists of 13,655 students and their learning logs (18,742,369 lines) in four semesters (from March 2017 to February 2019). In the first semester (i.e., March to July in 2017), all students must take about 6 courses (e.g., English, politics, distance learning, computer fundamentals, advanced mathematics, etc.).

In the Learner Overview (Fig. 2(b1)), they first find that the overall student engagement is lower than expectation. As shown in Fig. 2(b5), a large number of dots are densely distributed in the lower left corner of the chart, which indicates that most students have relatively low engagement with the LMS and course resources. As the number in x-axis increase, the density of dots decrease significantly, except for the area shown in Fig. 2(b4). EA explains that although students have a variety of factors that affect learning, they may view less videos than required number. In addition, the content of these videos may exceed the examination requirements; thus, viewing a few videos is sufficient for passing the exams and earning credit. However, the dense area shown in Fig. 2(b4) suggests a different student engagement patterns.

Using the interactive selector, they customize several groups of interested students in Fig. 2(b4), (b5) and (b6) for comparative exploration of their time management (i.e., corresponding to orange, blue and green groups in Fig. 2(a), (c) and (d)). As shown in Fig. 2(d1), most students in blue group have few online learning days and show no obvious temporal patterns. The online days of students in orange group is significantly higher than (d1), and it is characterized by 1-2 weeks of continuous intensive online learning in the middle of semester or before the final exams (Fig. 2(d2)). EB believes that this engagement distribution and corresponding learning calendars reflect a real learning phenomenon of procrastination. In addition, the students in green group spend more days on learning and show higher engagement than other groups (Fig. 2(d3)). Since the number of students in green group is small, domain experts browse each student's details in Learning Details View.

While browsing the green student group (i.e., those shown in Fig. 2(b6)), domain experts find some interesting patterns of multi-course time management, including the following: 1) self-regulated parallel learning: as a typical case shown in Fig. 3(a), these students regularly learn 4-5 courses per week and watch several videos per day; 2) self-regulated sequential learning: these students also learn regularly, but they will learn courses one by one and watch a lot of videos in one day (Fig. 3(b)); 3) procrastinated cram learning: although these students have spent many days on learning before exams, they rarely watched video completely and the progress of each course was lower (Fig. 3(c)). Both experts comment that these time management patterns may reflect different learning motivations and habits, which can be used for conducting teaching interventions, such as organizing offline discussions and providing support services. In addition, they consider providing these findings to school managers as a reference for improving the course design.

According to the feedbacks from our domain experts, LearnerVis still has room to improve. Although it could show the time management of one student, they have to browse many individuals to gain insight into the time management patterns of a group of students. Therefore, a primal improvement needed is to append the system with group analysis in future work.

7 Conclusion

In this paper, we present a visual analytics system called LearnerVis based on our proposed engagement calendar matrix model for exploring the time management of multi-course learning in online learning environment. A case study exemplifies the usefulness and the effectiveness of the design.

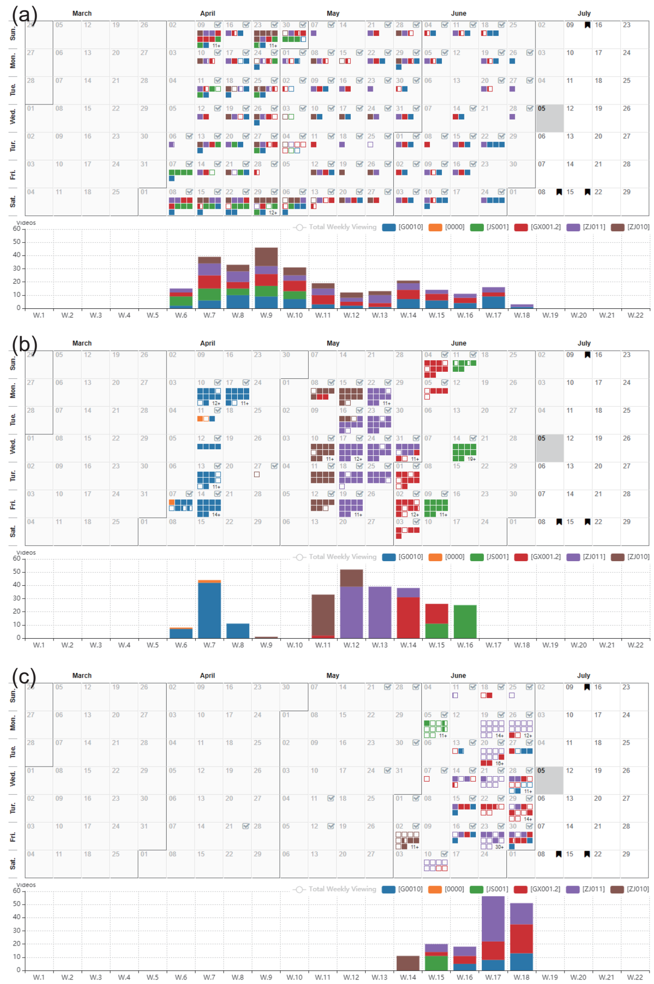

Figure 3: Three patterns of multi-course time management, including (a) self-regulated parallel learning, (b) self-regulated sequential learning, and (c) procrastinated cram learning.

Since the calendar-based visualization provides an intuitive representation of the periodicity of time series data, it may be applied to other domains. For instance, in sports and fitness, it can be used to visualize daily exercise to understand long-term exercise habits. Users, such as dietitians, can recommend training and diet plans based on the intensity of the exercise habits.

Acknowledgments

The authors would like to thank Dr. Rui Li and Dr. Haipeng Du,Prof. Weizhan Zhang and Prof. Chen Li for participating this project as domain experts and their feedbacks on our work, and the anonymous reviewers for their valuable comments of revising paper. This research was partially supported by "The Fundamental Theory and Applications of Big Data with Knowledge Engineering" under the National Key Research and Development Program of China with Grant No. 2018YFB1004500, the MOE Innovation Research Team No. IRT17R86, the National Science Foundation of China under Grant Nos. 61721002 and 61532015, the Project of China Knowledge Center for Engineering Science and Technology, and the Project of Shaanxi Education Informatization Development and Research No. 18JX005.

REFERENCES

[1] M. L. Bote-Lorenzo and E. Gómez-Sánchez. Predicting the Decrease of Engagement Indicators in a MOOC. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, LAK '17, pp. 143–147. ACM, New York, NY, USA, 2017. doi: 10.1145/3027385.3027387

[2] J. Broadbent and W. L. Poon. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, 27:1–13, 2015. doi: 10.1016/j.iheduc.2015.04.007

[3] Q. Chen, Y. Chen, D. Liu, C. Shi, Y. Wu, and H. Qu. PeakVizor: Visual Analytics of Peaks in Video Clickstreams from Massive Open Online Courses. *IEEE Transactions on Visualization and Computer Graphics*, 22(10):2315–2330, Oct. 2016. doi: 10.1109/TVCG.2015.2505305

[4] Q. Chen, X. Yue, X. Plantaz, Y. Chen, C. Shi, T. Pong, and H. Qu. ViSeq: Visual Analytics of Learning Sequence in Massive Open Online Courses. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–1, 2018. doi: 10.1109/TVCG.2018.2872961

[5] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD-96)*, pp. 226–231. AAAI Press, 1996.

[6] G. Fenu, M. Marras, and M. Meles. A Learning Analytics Tool for Usability Assessment in Moodle Environments. *Journal of e-Learning and Knowledge Society*, 13(3), Sept. 2017. doi: 10.20368/1971-8829/1388

[7] S. Fu, Y. Wang, Y. Yang, Q. Bi, F. Guo, and H. Qu. VisForum: A Visual Analysis System for Exploring User Groups in Online Forums. *ACM Trans. Interact. Intell. Syst.*, 8(1):3:1–3:21, Feb. 2018. doi: 10.1145/3162075

[8] S. Fu, J. Zhao, W. Cui, and H. Qu. Visual Analysis of MOOC Forums with iForum. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):201–210, Jan. 2017. doi: 10.1109/TVCG.2016.2598444

[9] P. J. Guo, J. Kim, and R. Rubin. How video production affects student engagement: an empirical study of MOOC videos. In *Proceedings of the First (2014) ACM Conference on Learning @ Scale*, pp. 41–50. ACM Press, 2014. doi: 10.1145/2556325.2566239

[10] K. F. Hew. Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology*, pp. 320–341, 2015. doi: 10.1111/bjet.12235

[11] K. Ilves, J. Leinonen, and A. Hellas. Supporting Self-Regulated Learning with Visualizations in Online Learning Environments. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education*, SIGCSE '18, pp. 257–262. ACM, New York, NY, USA, 2018. doi: 10.1145/3159450.3159509

[12] S. Joksimović, D. Gašević, T. M. Loughin, V. Kovanović, and M. Hatala. Learning at distance: Effects of interaction traces on academic achievement. *Computers & Education*, 87:204–217, Sept. 2015. doi: 10.1016/j.compedu.2015.07.002

[13] A. M. Kazerouni, S. H. Edwards, and C. A. Shaffer. Quantifying Incremental Development Practices and Their Relationship to Procrastination. In *Proceedings of the 2017 ACM Conference on International Computing Education Research*, pp. 191–199. ACM, Aug. 2017. doi: 10.1145/3105726.3106180

[14] R. F. Kizilcec, M. Pérez-Sanagustín, and J. J. Maldonado. Recommending Self-Regulated Learning Strategies Does Not Improve Performance in a MOOC. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale*, L@S '16, pp. 101–104. ACM, New York, NY, USA, 2016. doi: 10.1145/2876034.2893378

[15] R. F. Kizilcec, M. Pérez-Sanagustín, and J. J. Maldonado. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education*, 104:18–33, Jan. 2017. doi: 10.1016/j.compedu.2016.10.001

[16] G. C. Linderman, M. Rachh, J. G. Hoskins, S. Steinerberger, and Y. Kluger. Fast interpolation-based t-SNE for improved visualization of single-cell RNA-seq data. *Nature Methods*, 16(3):243, Mar. 2019. doi: 10.1038/s41592-018-0308-4

[17] J. Park, R. Yu, and F. Rodriguez. Understanding Student Procrastination via Mixture Models. In *Proceedings of the 11th International Conference on Educational Data Mining*, p. 11, 2018.

[18] C. Shi, S. Fu, Q. Chen, and H. Qu. VisMOOC: Visualizing video clickstream data from Massive Open Online Courses. In *2015 IEEE Pacific Visualization Symposium (PacificVis)*, pp. 159–166, Apr. 2015. doi: 10.1109/PACIFICVIS.2015.7156373

[19] F. Van der Sluis, J. Ginn, and T. Van der Zee. Explaining Student Behavior at Scale: The Influence of Video Complexity on Student Dwelling Time. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale*, L@S '16, pp. 51–60. ACM, New York, NY, USA, 2016. doi: 10.1145/2876034.2876051

[20] J. Xia and D. C. Wilson. Instructor Perspectives on Comparative Heatmap Visualizations of Student Engagement with Lecture Video. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education*, SIGCSE '18, pp. 251–256. ACM, New York, NY, USA, 2018. doi: 10.1145/3159450.3159487

[21] M. Yamada, Y. Goda, T. Matsuda, Y. Saito, H. Kato, and H. Miyagawa. How does self-regulated learning relate to active procrastination and other learning behaviors? *Journal of Computing in Higher Education*, 28(3):326–343, Dec. 2016. doi: 10.1007/s12528-016-9118-9

[22] T.-C. Yang, M. C. Chen, and S. Y. Chen. The influences of self-regulated learning support and prior knowledge on improving learning performance. *Computers & Education*, 126:37–52, Nov. 2018. doi: 10.1016/j.compedu.2018.06.025