VUC: Visualizing Daily Video Utilization to Promote Student Engagement in Online Distance Education

Huan He
SPKLSTN Lab, School of EIE
Xi'an Jiaotong University
Xi'an, Shaanxi, China
hehuan@mail.xjtu.edu.cn

Bo Dong
School of Continuing Education
National Engineering Lab for Big Data Analytics
Xi'an Jiaotong University
Xi'an, Shaanxi, China
dong.bo@mail.xjtu.edu.cn

Qinghua Zheng
SPKLSTN Lab, School of EIE
Xi'an Jiaotong University
Xi'an, Shaanxi, China
qhzheng@mail.xjtu.edu.cn

Guobin Li
Beijing National Center For
Open & Distance Education Co., LTD
Beijing, China
ligb@mail.open.com.cn

ABSTRACT

Online video is a widely used learning resource in various courses in online distance education (ODE). For the students who are in an undergraduate program in ODE, it is challenging to study multiple online courses and keep track of the video viewing progress each semester. In this paper, we introduce a viewing progress visualization tool called video utilization calendar (VUC) for promoting student engagement with the videos of multiple online courses. VUC is designed to visualize both the current viewing progress and the daily viewing history for all the courses in a semester based on measurements of video utilization. Using the visualized interface, students can check their viewing progress for all videos and choose any course video to view directly. To evaluate VUC, we conducted a randomized controlled trial and a survey in an ODE school. Our results demonstrate that students may spend more days online and view more course videos with the support of VUC, whereas the total video viewing time does not increase significantly. In addition, with the help of VUC, course instructors identified two patterns of video utilization; hence, VUC may also be of assistance to instructors in understanding how students schedule their video viewing for multiple courses and personalizing the learning process for students.

CCS CONCEPTS

• **Human-centered computing → Visualization**; **Visualization systems and tools**; • **Applied computing → Education**; *Learning management systems*; E-learning;

KEYWORDS

Distance education, video utilization, visualization

CompEd'19, May 17-19, 2019, Chengdu, China

ACM ISBN 978-1-4503-5103-4/18/02.
https://doi.org/10.1145/1234567.1234567

1 INTRODUCTION

Online distance education (ODE) has become an important supplement to higher education in recent years, which provides students across the country with the opportunity to access high-quality educational resources [18]. In online learning and ODE, student engagement is considered a necessary prerequisite for learning, retention, achievement and graduation [12, 13, 20, 22]. Scholars have typically identified student engagement as a construct that consists of three components: behavioral engagement, emotional engagement, and cognitive engagement [10, 13]. Our work focuses on students' behavioral engagement and throughout this paper, "engagement" will refer to "behavioral engagement".

With the support of a learning management system (LMS), students' online activities (e.g., viewing and posting) can be recorded and saved as log data, which is a potential data source for measuring student engagement. By mining this log data, studies of student engagement in online learning environments have identified multiple factors that affect student engagement, such as video production [11], virtual achievement badges [1, 9], embedding discussion threads into video [26], and discussion activities [8]. Based on these findings, both student engagement and learning experience can be improved to achieve a better learning outcome. Moreover, several studies have demonstrated that improving the design or visualization function of the LMS may also have an impact on student engagement [2, 14, 20].

In this study, we describe our experience of using a visualization tool to promote student engagement with online video lectures for multiple courses. Since online videos are the main learning materials in the undergraduate program of our ODE school, each ODE student must view many videos on the LMS to obtain knowledge and skills (approximately 1,300 videos of 24 courses in 4 semesters over 2 years). Therefore, improving the LMS to promote student engagement with video lectures is of interest to the ODE school.

To address this issue, we developed a visualization tool called video utilization calendar (VUC), with reference to existing research on student engagement and visualization [2, 4, 11, 14, 24] in online learning environments. VUC is designed to help students understand their viewing progress for multiple courses by showing the video utilization from three aspects: the viewing progress for all courses, the daily viewing history during the semester, and the weekly viewing statistics. Moreover, we discussed the results of the experiment and the survey and analyzed the viewing histories of students in experiment with two course instructors.

The main contributions of this paper are as follows:

- We developed an online visualization tool for helping students understand and improve their video utilization for multiple courses in online learning environments.
- We conducted a randomized controlled trial and a survey to evaluate the effectiveness and usefulness of VUC.
- Two patterns of viewing history were identified in the visual analysis of video utilization using VUC.

2 RELATED WORK

In this section, we review the literature that is related to student engagement in online learning environments. Then, we summarize recent works on using visualization in online learning and discuss how our tool extends prior works.

2.1 Student Engagement

To measure student engagement in online learning environments, many metrics have been proposed from various perspectives. The most commonly used metrics for measuring student engagement are based on student interactions with functions and resources in the LMS. Guo et al. [11] used the time that a student spends on a video and whether a student attempts the follow-up problem after watching a video as proxies for engagement. Singh et al. [23] proposed a content engagement score for measuring the engagement by the students with specified content, which consists of cognitive, emotional, and behavioral engagement, using a comprehensive set of user activities. Van der Sluis et al. [24] 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 interaction with educational videos. Bote-Lorenzo and Gómez-Sánchez [4] defined 16 metrics for measuring student engagement in each chapter of an online course, such as the percentage of lecture videos that were totally or partially watched, the percentage of finger exercises that were answered, and the percentage of assignments that were submitted.

The promotion methods and the factors that influence engagement are also the focus of many studies. For example, Kovacs [17] found that in-video quizzes have the potential to improve engagement by making lectures more interactive. Van der Sluis et al. [24] proposed using the information rate to measure the video complexity and found there was a polynomial relationship between the video complexity and the student dwelling time. Brunskill et al. [5] suggested that providing a default option may encourage students to attempt to solve more practice problems. Zhao et al. [26] proposed reusing past high-value discussion threads in future lecture video and found that this approach was useful to students. Guo et al. [11] found that shorter videos, informal talking-head videos, high-enthusiasm videos and Khan-style videos are more engaging. Moreover, there are many other factors that may affect online learning engagement, such as cohort size of the forum [3], academic self-efficacy, teaching presence, perceived usefulness [16], the instructor's course preparation, guidance and assistance [21].

Previous studies have provided a variety of metrics that are related to course videos for measuring the student engagement. We plan to use viewing-related metrics in VUC with reference to existing metrics and methods [4, 11, 24] to improve the video utilization of ODE students.

2.2 Online Learning Visualization

Visualization tools have been widely used in online learning environments to improve the instructional design and the learning experience. On the one hand, instructors can use visual analytic tools to explore patterns in large-scale online learning. For example, Coffrin et al. [7] used bar charts, line charts and state transition diagram to help instructors understand learner behaviors. Chen et al. [6] developed a visualization system called PeakVizor to investigate viewing patterns in clickstream data. Xia and Wilson [25] developed a comparative heatmap tool that enabled instructors to explore and compare student video engagement.

Using visual aids can also support students' online activities. Ilves et al. [14] used a radar chart to support self-regulated learning and found that the lowest-performing students can benefit from this visualization. Ishizue et al. [15] presented a program visualization tool called PlayVisualizerC for novice C language programmers that facilitates learning the concept of memory management. Liu et al. [20] developed a learning analytic system called Tracer to promote student engagement by visualization feedback of behavioral patterns in writing activities. Auvinen et al. [2] used heatmap to show a prediction of students' success based on their behaviors. In addition, studies have found that visual achievement badges can have a positive impact on students' online learning activities [1, 2, 9].

In summary, these works apply a variety of visualization and interactive techniques in online learning, which inspires the design of VUC. However, these approaches are mainly designed for use in single courses, while ODE students take multiple courses at the same time. Hence, a multiview visualization tool must be developed to help ODE students understand their video utilization and viewing history for multiple courses.

3 OVERVIEW OF VUC

3.1 Video Utilization and Measurements

Students can access various learning resources on the LMS, including videos, slides, and textbooks. Among these learning resources, video is the main learning material. Consider the computer science and technology major in our ODE school as an example: There are 23 courses for each student to take in 4 semesters over 2 years, including foundation courses (e.g., English and discrete mathematics) and core courses (e.g., computer networks and operating systems), which involve 1,491 videos of 773 hours in total length. Therefore, each student must take 5-7 courses each semester.

However, the LMS that is currently used in our ODE school only provides the record of the last video that was viewed for a single course. Students can view neither the utilization of each video nor the viewing history for all of their courses. Therefore, we plan to develop a visualization tool that displays both the viewing progress and the daily viewing history for multiple courses to help students improve their video utilization. We use the following metrics to describe student video utilization as a proxy for student engagement and display them in VUC:

- *Video Attendance Rate (AR)* measures whether a student viewed a video or not. If a student viewed a video, the video AR is 1; otherwise, it is 0.
- *Video Utilization Rate (UR)* measures the proportion of a video that has been viewed by a student.
- *Course AR* measures the ratio of the number of viewed videos to the total number of videos in a course by a student.
- *Course UR* measures the ratio of the total time spent by a student viewing videos to the total video duration in a course.
- *Weekly viewing* measures the total number of videos a student viewed during a week.

3.2 System Architecture

As shown in Figure 1, the architecture of VUC consists of three components: a data analysis module, a data storage module, and a visualization module.

Data Analysis Module: This module includes two submodules: a data collection and preprocessing module, which collects data from the LMS, and a video utilization statistics module, which analyzes students' daily video utilization. We write several Python scripts that implement each submodule and deploy them as scheduled tasks on the VUC server. These scripts are executed automatically at 1:00 am every day to calculate the five metrics for the previous day.

Storage Module: In addition to saving the course data and cleared log data, this module also saves the statistical results to facilitate access from the visualization module.

Visualization Module: This module is a web-based application that enables students to check their viewing progress from various aspects. To facilitate students' use of VUC, we integrate the visualization module into the LMS by embedding the GUI as a panel called *My Viewing Calendar* on the student dashboard page. As a result, students will see their viewing progress immediately after login to the LMS. The GUI of this module is developed with HTML5, JavaScript and open-source libraries (including ECharts [19] and Vue.js[1]), and its source code has been opened as a standalone web application on GitHub [2] for demonstration.

3.3 VUC Design

To provide students with an intuitive impression of the progress in all courses, we design three visualizations that display video utilization from various aspects: a course progress table, a video viewing calendar and a weekly viewing chart. Figure 2 is a screenshot of the video utilization of a student who was involved in this study for six courses in one semester, which shows the interface of VUC.

Course Progress Table: As discussed in Section 3.1, each ODE student needs to observe the viewing progress for all courses in which he/she is enrolled in the semester. Therefore, we design a table that lists all the videos of the courses in which a student is enrolled as cells (Figure 2(a)). We map the video utilization to the

[1] An open-source JavaScript framework. https://vuejs.org/
[2] Source code of VUC: https://github.com/hehuan2112/VideoUtilizationCalendar

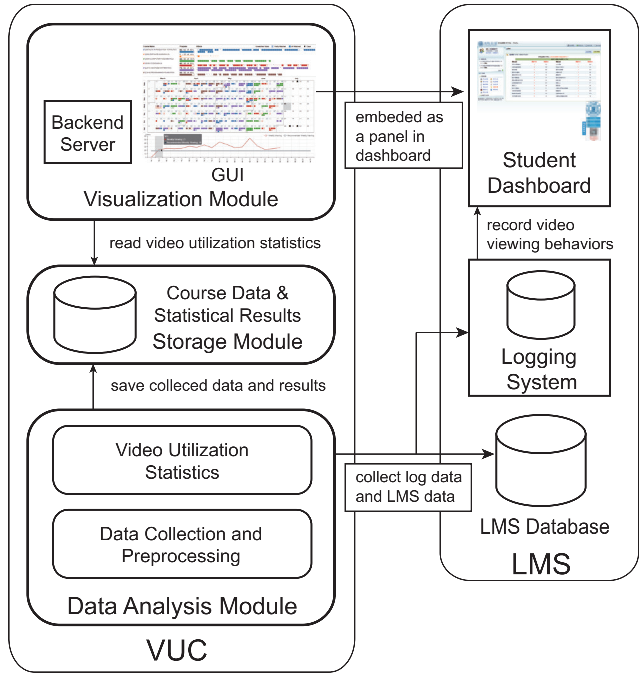

Figure 1: Overview of the VUC architecture

style of each cell with the AR and UR metrics, which are defined in Section 3.1. In this table, each course is assigned a color, which is used to distinguish the video cells in this table and the calendar below. The viewing progress of each course is displayed in each row, which contains three columns. The first column shows the course name. The second column shows the number of viewed videos and the course AR in a progress bar. The last column shows the utilization of each video in the course using a square cell of a different style, which is illustrated in Figure 2(d): an unwatched video is represented as a blank cell with a dashed border (the video AR is 0), while a watched video is represented as a cell with a solid border (the video AR is 1). The video UR is mapped to the width of the inner color block of the cell.

Video Viewing Calendar: As shown in Figure 2(b), we design a calendar-based layout for visualizing the daily video utilization, which shows a student's viewing history over the entire semester. The visual design of this interface is consistent with the printed version of curriculum calendar that students received in each semester. In each date cell, a check-in icon in the upper-right corner indicates that the student has viewed at least one video on that day. Meanwhile, all the videos that were viewed that day are listed in the date cell. When the course exam date is determined, there will be a black mark in the upper right corner of the corresponding date cell (as shown in the cells of July 8, 9 and 15 in Figure 2(b)).

Weekly Viewing Chart: Based on the detailed video viewing history, we use a line chart to illustrate the weekly viewing trend (the red line in Figure 2(c)). The horizontal axis of this chart represents the weeks in the semester, where each bin corresponds to a column in the calendar that is described above (e.g., as shown in Figure 2(c), the bin of week 2 corresponds to the week of March 5 to 11 in the calendar). In addition, we add a reference line for weekly

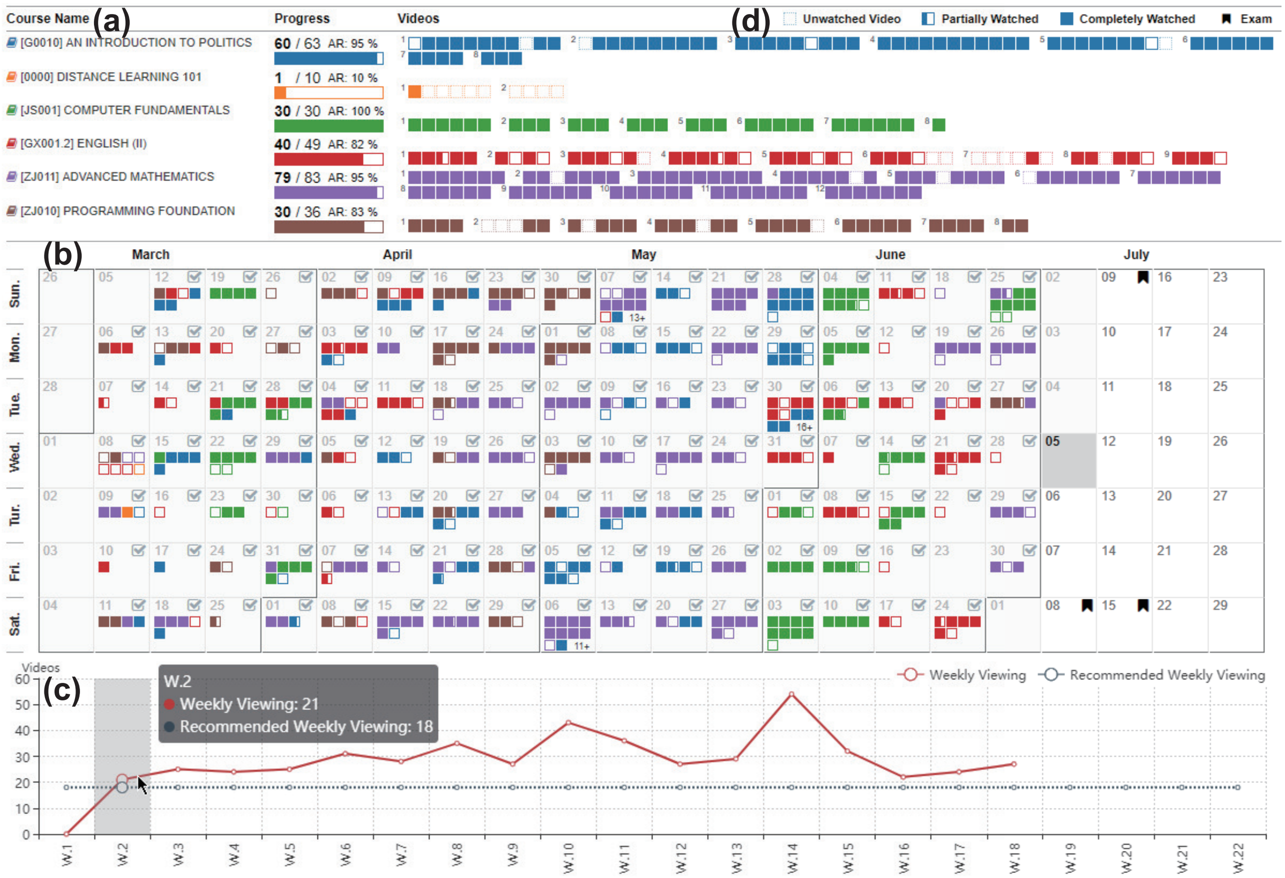

Figure 2: Screenshot of the visualization module of VUC, which includes: (a) a course progress table showing the viewing progress of all courses and all videos, (b) a video viewing calendar revealing viewing activities in each day, and (c) a weekly viewing chart showing something that is important for student to figure out learning history. (d) Legend of the cell and mark.

viewing in this chart (the blue dotted line in Figure 2(c)), the value of which is recommended by the ODE school.

4 EVALUATION

We investigate the following research questions (RQs):

- **RQ1** Does displaying the video viewing progress with VUC have a significant effect on students' video utilization?
- **RQ2** Is VUC useful for students who are taking multiple online courses?

A randomized controlled trail and a survey were conducted to evaluate VUC with respect to RQ1 and RQ2.

4.1 Context

The data that were used in this study come from the undergraduate program of computing in the ODE school of our university. This program runs from March 2017 to February 2019, with a total of 4 semesters. In the first semester, students must take 6 courses (which include English, computer fundamentals, and programming foundation, as shown in Figure 2 (a)). At the end of the semester, they must pass the course exams to earn credits.

In Spring 2017, 751 students were enrolled in this program, of whom 327 were included in this study. These students are aged between 20 and 45 (M = 27.9, SD = 4.7), and their academic qualifications at the time of enrollment are high school or equivalent. The remaining 424 students were excluded due to a restricted learning environment (e.g., a low-bandwidth network), in which they used offline videos for learning. VUC can neither collect their log data nor display their viewing progress. The 327 students were divided randomly into two groups: The control group consisted of 164 students who were not shown VUC and the treatment group consisted of 163 students who were shown VUC.

4.2 Method

At the beginning of the semester, few learning data have been recorded by the LMS since students spent approximately 2 weeks carrying out school affairs, such as entrance exams, payment, and receiving learning materials. Therefore, we enabled VUC in the LMS for the treatment group starting the 3rd week. Throughout the semester, the students in the treatment group can use VUC to view their video utilization at any time. At the end of the semester, we collected log data of all students in this study from the LMS and sent an online questionnaire to the students of the treatment group.

Table 1: Questions in the questionnaire about usefulness

#	Question
Q1	Do you think the visualization of videos and courses in VUC is easy to understand?
Q2	Do you think VUC is useful for checking your viewing progress and history of your courses?
Q3	Do you think VUC is helpful in promoting your viewing progress of multiple courses?

The questions in the questionnaire are listed in Table 1, which are evaluated on a scale from 1 (strongly disagree) to 5 (strongly agree). In addition, they were asked the following open-ended question: Please provide your comments or suggestions regarding VUC.

The following three metrics are used to measure the student engagement in the semester: *Semester AR*, *Semester UR*, and *Active Days*. *Semester AR* measures the mean course AR of each of the 6 courses over the semester; *Semester UR* measures the mean course UR of each of the 6 courses over the semester; and *Active Days* measures the number of days that were spent viewing videos online during the semester.

5 RESULTS AND DISCUSSION

5.1 Evaluation

Table 2 lists the statistical results of the three metrics for the control group and the treatment group. Figure 3 illustrates the distributions of the three metrics for the two groups. Figure 4 shows the distribution of students' answers to Q1-Q3 (131 of 163 responded), which are used to evaluate the usefulness of VUC.

RQ1: We conducted the Shapiro–Wilk test on each metric of two groups, which shows that none of the metrics follows a normal distribution ($p < 0.001$). Figure 3 and Table 2 show that the treatment group has higher semester AR and active days, on average, with higher standard deviations than the control group. Table 2 also shows the p-value between the two groups using the Mann–Whitney–Wilcoxon test. The differences in the semester AR and active days between the two groups are statistically significant ($p < 0.05$ and $p < 0.01$), while the difference in the semester UR is not statistically significant ($p = 0.152$). In addition,

The results demonstrate that although the overall engagement is low, using VUC does promote the engagement slightly. The treatment group viewed more videos and spent more days online than the control group. However, the total viewing time did not increase significantly as the number of views increased. This difference may imply that although students of the treatment group opened more videos when using VUC, they only viewed them for a short time. Since the activities after opening videos are beyond the scope of VUC, this finding suggests that although VUC encourages students to view more videos for multiple courses, there are other factors that can further affect the time that is spent viewing videos.

RQ2: As shown in Figure 4, approximately 90% of the students feel that VUC is easy to understand (Q1) and approximately 83% of the students feel that VUC is useful in promoting their course progress, while approximately 13% do not (Q2 and Q3). In the open-ended question, most students give positive comments on VUC, such as *"the chart is simple and intuitive"*, *"the calendar is very helpful for me to arrange study time"*, and *"it is easy to find out which videos I have not watched"*. In addition, students also describe the issues that are encountered when using VUC. We summarize these comments as follows:

- *The video I just watched doesn't appear*: Some students want to check the videos they just viewed; however, VUC doesn't behave as expected. We will improve this in the future.
- *I don't know which video to watch next*: These students have difficulty choosing the videos to watch when they schedule a study plan according to the viewing calendar. They expect VUC to provide suggestions about when and which videos to watch. We plan to add more interactive tips for the interface and send direct notifications by instant massager to guide students through the videos.
- *There are too many unwatched videos, I give up*: These students no longer watch any videos due to limited study time when they find that there are many unwatched videos in VUC. They suggest that VUC should mark the videos that involve key points in the exam to reduce the number of videos that must be watched.

Table 2: Statistics on three metrics for two groups

Metric	Control Group Median(Mean, SD)	Treatment Group Median(Mean, SD)	MWW Test
Semester AR	0.049 (0.112, 0.135)	**0.094** (0.137, 0.152)	<0.05
Semester UR	0.035 (0.132, 0.224)	**0.061** (0.134, 0.205)	0.152
Active Days	6.0 (10.4, 10.7)	**10.0** (13.4, 14.3)	<0.01

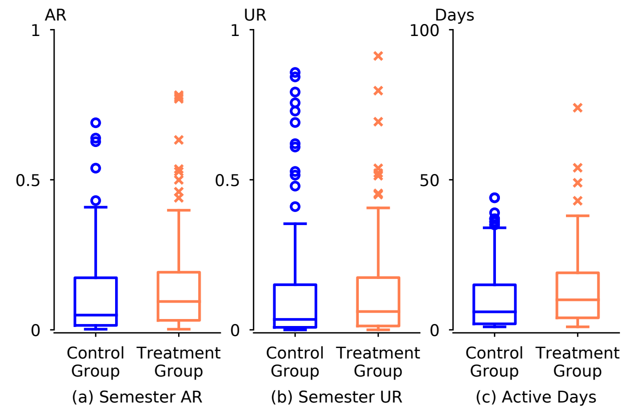

Figure 3: Box plot of the distribution of each metric in two groups. (a) Semester AR. (b) Semester UR. (c) Active Days.

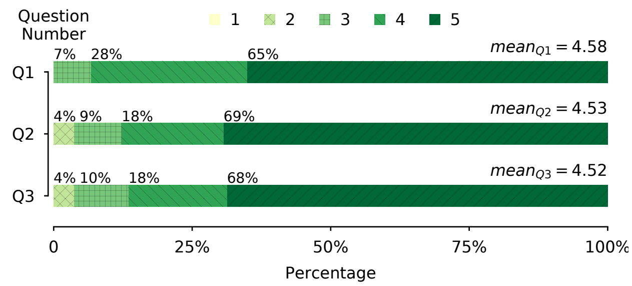

Figure 4: Results of Q1-Q3 (N=131).

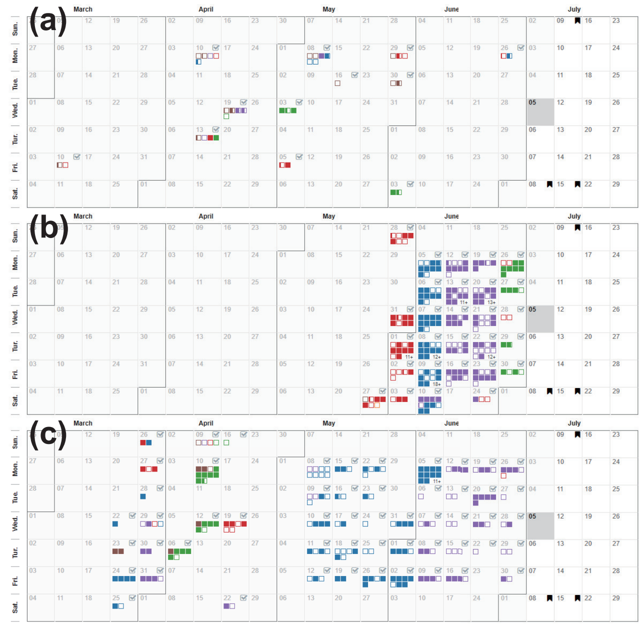

Figure 5: Different patterns of viewing history. (a) An example of s student spent a few days online. (b) "cram session" pattern. (c) "long-term learning" pattern .

The results indicate that VUC is helpful for promoting video utilization for ODE students, but there is still a gap between the present functionality and the students' expectations. Since most ODE students have jobs on weekdays, their study time is very limited. The existing features of VUC can only help them understand the past viewing status and do not provide further assistance. The results also demonstrate that students may need more guidance or recommendations (e.g., a weekly video viewing plan and an important video list) from the LMS to help them manage their video viewing. Especially when their viewing progress falls behind relative to the plan, they may benefit from the help of the LMS.

5.2 Engagement Pattern Analysis

To further evaluate VUC, we collaborated with two course instructors (IA and IB) during the experiment. Both of them are from the ODE school and have prior experience with VUC. At the end of the semester, we collected the VUC screenshots of all students in this study, and then performed interviews with IA and IB. During the interview, the screenshots were shown in ascending order of active days to them for analysis of the engagement pattern throughout the semester. We collected their feedback and discussion as follows.

First, they found that the overall video utilization was lower than expected for the ODE school. As shown in Figure 3, both the semester AR and the semester UR of most students were less than 50%, which means that more than 50% of the course videos were not viewed. IA explained that although students had a variety of factors that affect learning, they should view at least a third of the videos. 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. Hence, there may be a mismatch between the current videos and the needs of the students. Therefore, IA and IB considered providing these results to ODE managers as a reference for improving the course design.

Second, as shown in Figure 5(a), for most students, no pattern is identified since they spent only a few days online. However, for students with more active days, two interesting patterns are identified: (1) the "*cram session*" pattern: these students begin viewing videos almost every day approximately a month before the exam (Figure 5(b)) and (2) the "*long-term learning*" pattern: as shown in Figure 2(b) and Figure 5(c), these students view videos for most weeks throughout the semester. IA commented that these utilization patterns may reflect different learning motivations and habits, which can be used for recommending learning materials.

5.3 Limitations

The following internal and external validity concerns are raised: Although all the students in this study have the same academic background and major, their motivation, learning ability, work experiences and learning environments vary. For example, some students have been working for many years, while others have just graduated from high school. The experienced students may perform better in these self-paced courses. In addition, it is possible that some students are in an environment with a poor network connection, which would affect their online learning.

The results may depend on course arrangement, course content, and the ODE school's requirement. Other majors may have fewer courses and videos each semester and the content may be more suitable for students' needs. In some ODE schools, the number of viewed videos or the time that is spent viewing videos is counted as part of the students' grades, in which case students are incentivized to open many videos, even if they are not watching them.

6 CONCLUSION AND FUTURE WORK

In this paper, we presented a visualization tool called VUC for visualizing the video utilization of multiple online courses to help students improve their viewing progress. We conducted a randomized controlled trial and a survey to evaluate VUC. The results demonstrated that VUC was helpful for students in terms of viewing more videos and spending more days online, while the viewing time was not affected. In addition, two patterns were identified by course instructors with the support of VUC; hence, VUC may be of assistance to instructors in determining how students schedule their video viewing throughout the semester.

In the future, we will continue to improve VUC by implementing a real-time viewing progress functionality to help students check their current video viewing times. Moreover, we plan to recommend video lectures in VUC and send notifications by instant massager to help students schedule their online learning.

ACKNOWLEDGMENTS

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, 61532015, and Project of China Knowledge Center for Engineering Science and Technology.

REFERENCES

[1] Ashton Anderson, Daniel Huttenlocher, Jon Kleinberg, and Jure Leskovec. 2014. Engaging with Massive Online Courses. In *Proceedings of the 23rd International Conference on World Wide Web (WWW '14)*. ACM, New York, NY, USA, 687–698. https://doi.org/10.1145/2566486.2568042

[2] T. Auvinen, L. Hakulinen, and L. Malmi. 2015. Increasing Students' Awareness of Their Behavior in Online Learning Environments with Visualizations and Achievement Badges. *IEEE Transactions on Learning Technologies* 8, 3 (July 2015), 261–273. https://doi.org/10.1109/TLT.2015.2441718

[3] Jiye Baek and Jesse Shore. 2016. Promoting Student Engagement in MOOCs. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale (L@S '16)*. ACM, New York, NY, USA, 293–296. https://doi.org/10.1145/2876034.2893437

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

[5] Emma Brunskill, Dawn Zimmaro, and Candace Thille. 2018. Exploring the Impact of the Default Option on Student Engagement and Performance in a Statistics MOOC. In *Proceedings of the Fifth Annual ACM Conference on Learning at Scale (L@S '18)*. ACM, New York, NY, USA, 34:1–34:4. https://doi.org/10.1145/3231644.3231692

[6] Qing Chen, Yuanzhe Chen, Dongyu Liu, Conglei Shi, Yingcai Wu, and Huamin Qu. 2016. PeakVizor: Visual Analytics of Peaks in Video Clickstreams from Massive Open Online Courses. *IEEE Transactions on Visualization and Computer Graphics* 22, 10 (Oct. 2016), 2315–2330. https://doi.org/10.1109/TVCG.2015.2505305

[7] Carleton Coffrin, Linda Corrin, Paula de Barba, and Gregor Kennedy. 2014. Visualizing Patterns of Student Engagement and Performance in MOOCs. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge (LAK '14)*. ACM, New York, NY, USA, 83–92. https://doi.org/10.1145/2567574.2567586

[8] R. Wes Crues, Nigel Bosch, Michelle Perry, Lawrence Angrave, Najmuddin Shaik, and Suma Bhat. 2018. Refocusing the Lens on Engagement in MOOCs. In *Proceedings of the Fifth Annual ACM Conference on Learning at Scale (L@S '18)*. ACM, New York, NY, USA, 11:1–11:10. https://doi.org/10.1145/3231644.3231658

[9] Paul Denny. 2013. The Effect of Virtual Achievements on Student Engagement. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 763–772. https://doi.org/10.1145/2470654.2470763

[10] Jennifer A Fredricks, Phyllis C Blumenfeld, and Alison H Paris. 2004. School Engagement: Potential of the Concept, State of the Evidence. *Review of Educational Research* 74, 1 (March 2004), 59–109. https://doi.org/10.3102/00346543074001059

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

[12] Curtis R. Henrie, Lisa R. Halverson, and Charles R. Graham. 2015. Measuring student engagement in technology-mediated learning: A review. *Computers & Education* 90 (Dec. 2015), 36–53. https://doi.org/10.1016/j.compedu.2015.09.005

[13] Khe Foon Hew. 2015. Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology* (2015), n/a–n/a. https://doi.org/10.1111/bjet.12235

[14] Kalle Ilves, Juho Leinonen, and Arto Hellas. 2018. Supporting Self-Regulated Learning with Visualizations in Online Learning Environments. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18)*. ACM, New York, NY, USA, 257–262. https://doi.org/10.1145/3159450.3159509

[15] Ryosuke Ishizue, Kazunori Sakamoto, Hironori Washizaki, and Yoshiaki Fukazawa. 2018. PVC: Visualizing C Programs on Web Browsers for Novices. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18)*. ACM, New York, NY, USA, 245–250. https://doi.org/10.1145/3159450.3159566

[16] Yeonji Jung and Jeongmin Lee. 2018. Learning engagement and persistence in massive open online courses (MOOCS). *Computers & Education* (Feb. 2018). https://doi.org/10.1016/j.compedu.2018.02.013

[17] Geza Kovacs. 2016. Effects of In-Video Quizzes on MOOC Lecture Viewing. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale (L@S '16)*. ACM, New York, NY, USA, 31–40. https://doi.org/10.1145/2876034.2876041

[18] Kyungmee Lee. 2017. Rethinking the accessibility of online higher education: A historical review. *The Internet and Higher Education* 33 (April 2017), 15–23. https://doi.org/10.1016/j.iheduc.2017.01.001

[19] Deqing Li, Honghui Mei, Yi Shen, Shuang Su, Wenli Zhang, Junting Wang, Ming Zu, and Wei Chen. 2018. ECharts: A declarative framework for rapid construction of web-based visualization. *Visual Informatics* 2, 2 (June 2018), 136–146. https://doi.org/10.1016/j.visinf.2018.04.011

[20] M. Liu, R. A. Calvo, A. Pardo, and A. Martin. 2015. Measuring and Visualizing Students' Behavioral Engagement in Writing Activities. *IEEE Transactions on Learning Technologies* 8, 2 (April 2015), 215–224. https://doi.org/10.1109/TLT.2014.2378786

[21] Jing Ma, Xibin Han, Juan Yang, and Jiangang Cheng. 2015. Examining the necessary condition for engagement in an online learning environment based on learning analytics approach: The role of the instructor. *The Internet and Higher Education* 24 (2015), 26–34. https://doi.org/10.1016/j.iheduc.2014.09.005

[22] Trang Phan, Sara G. McNeil, and Bernard R. Robin. 2015. Students' Patterns of Engagement and Course Performance in a Massive Open Online Course. *Computers & Education* (Dec. 2015). https://doi.org/10.1016/j.compedu.2015.11.015

[23] Vivek Singh, Balaji Padmanabhan, Triparna de Vreede, Gert-Jan de Vreede, Stephanie Andel, Paul E. Spector, Steve Benfield, and Ahmad Aslami. 2018. A Content Engagement Score for Online Learning Platforms. In *Proceedings of the Fifth Annual ACM Conference on Learning at Scale (L@S '18)*. ACM, New York, NY, USA, 25:1–25:4. https://doi.org/10.1145/3231644.3231683

[24] Frans Van der Sluis, Jasper Ginn, and Tim Van der Zee. 2016. 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)*. ACM, New York, NY, USA, 51–60. https://doi.org/10.1145/2876034.2876051

[25] Jinyue Xia and David C. Wilson. 2018. 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)*. ACM, New York, NY, USA, 251–256. https://doi.org/10.1145/3159450.3159487

[26] Qian Zhao, Sashank Varma, and Joseph A. Konstan. 2017. In-Video Reuse of Discussion Threads in MOOCs. In *Proceedings of the Fourth (2017) ACM Conference on Learning @ Scale (L@S '17)*. ACM, New York, NY, USA, 153–156. https://doi.org/10.1145/3051457.3053972