VIDEO-PLAYING LOGS FOR ANALOGOUS VIDEOS REVEAL LEARNERS' PROACTIVE LEARNING STRATEGIES

Satoshi Yazawa[1], Masashi Inutsuka[2], Terutaka Komahashi[3], Kento Kanemura[1] and Kazuo Hiraki[1]
[1]*Graduate School of Arts and Sciences, The University of Tokyo, Meguro-ku, Tokyo, Japan*
[2]*Samuraikyoiku Co., Bunkyo-ku, Tokyo, Japan*
[3]*E Cubed (Online English School), Yokohama City, Kanagawa, Japan*

ABSTRACT

On-demand lecture videos play a major role in the networked classroom environment. However, there have not been many studies on the methods for optimal lecture video production as the mainstream approach is to statistically analyze indicators such as video length, playback speed, and the number of operations based on viewing records of existing lecture videos like MOOCs. We collaborated with an English lecture specialist to perform a controlled experiment by creating two videos with the same topic, lecturer, and studio, but different editing policies. By analyzing the detailed logs, we found that the number of points increased with learning time for the learners who viewed the lecture videos edited in the form of explicit chapters, and that learners changed their behavior such as seeking and changing the playback speed, depending on the video editing policy and their own ability. This suggests that it is important for lecture video creators to organize chapters and design user interfaces based on the assumption that learners will actively seek to optimize their viewing behavior according to their abilities.

KEYWORDS

Learning analytics, On-demand lecture video

1. INTRODUCTION

On-demand lecture videos are increasingly being used as an auxiliary tool in situations where face-to-face teaching is no longer possible due to the COVID-19 pandemic (Impey, 2021). Lectures using on-demand video are the primary form of educational material for online educational services, such as MOOCs (Massive Open Online Courses) (Baturay, 2015). Since MOOCs have been reported to have high dropout rates (Onah, 2014), ways to improve lecture videos and obtain high retention rates has become an important issue. One approach to improving such lecture videos and other learning materials is learning analytics. Learning analytics is the measurement, collection, analysis, and use of learner data and their situations for the purpose of understanding and optimizing learning content and its environment (Long, 2011). It has been mentioned that most learning analytics studies have analyzed learner behavior, but only a few have addressed the improvement of learning materials (Zhu, 2022).

A study focusing on learners' video viewing behavior reported that learners who played the video at 1.25x speed received more certificates than those who played it at 1x speed when an intervention was used to change default playback speed (Lang, 2020). A playback speed of 1.25x was found to be optimal for the group with low prior mastery regarding lecture videos, but that of 1.5x helps the group with higher mastery obtain better learning effects (Mo, 2022). It is unclear, however, how these trends change with the content and style of lecture videos. A study that focused on improving lecture videos analyzed the relationship between lecture videos and engagement from MOOC logs (Guo, 2014). The researchers used video playback time normalized by video length as a measure of engagement, and evaluated videos shorter than three minutes as having high engagement. However, it is unclear how the seek bar and playback speed change functionality of the video player affects engagement and learning effectiveness. The lack of studies on the characteristics of lecture videos could be due to the lack of variety in teaching materials relative to the differences in learners' learning abilities. In other words, it is difficult to estimate how factors other than the length of the video, such as the speaker's appearance, speaking style, presentation technique, filming technique, and editing technique, affect the learning log if there are two video materials on the same subject.

Therefore, in cooperation with a professional instructor who creates videos, we conducted a comparative experiment using two types of video materials on the same subject with partially different editing policies. In particular, we focus on the presence or absence of clear chapter division in lecture videos as an editing policy. We analyze how learners' behavior changes with and without chapter division according to their own level of understanding, how learning effects change, and what elements are necessary for an effective lecture video to be usable by learners.

2. MATERIALS AND METHODS

Subjects were asked to take a pre-test prior to the experiment and a post-test immediately after watching a lecture video. The two types of lecture videos were randomly assigned to the subjects. The task sequence presented to the subjects and the type of lecture video are shown in Figure 1.

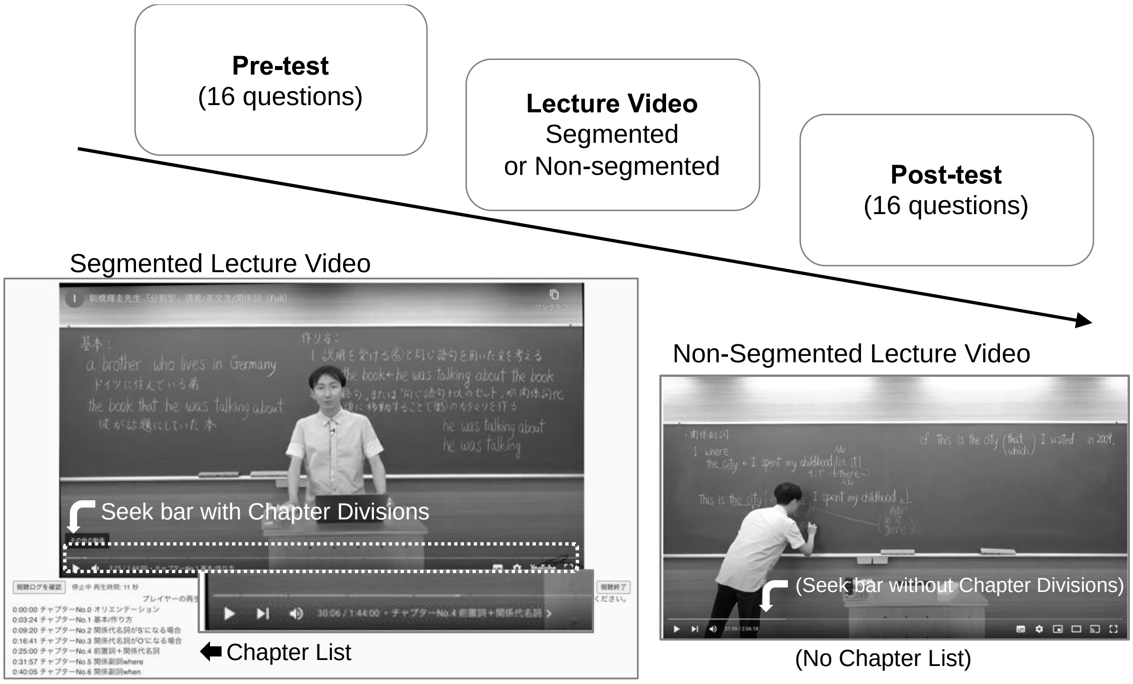


Figure 1. Task flow and prepared lecture videos

Two types of lecture videos (segmented and non-segmented) on the theme of relative pronouns in English grammar were prepared. These videos were created by co-author Komahashi, a professional cram school teacher. Each video showed a lecture by Komahashi himself, performed in the same studio, and filmed in the same location. The segmented video is divided into chapters explaining each topic, and chapter information was added for easy headings. In contrast, the non-segmented video is a video recording of a lecture, which includes the writing on the blackboard. The subjects' behavior toward these videos were compared. Komahashi also created two types of quizzes to check comprehension: a pre- and post-test with four choices. The content of the pre-test and post-test was the same for all subjects. Each test displayed the correct and incorrect answers and total score for each question immediately after the answers.

2.1 Design of Lecture Video

The lecture video consists of 15 topics for both the segmented and non-segmented videos. The list of topics is shown in Table 1.

Table 1. List of video topics. Each type of video has different lengths of topics

No	Title	Duration (Non-segmented; board writing; sec)	Duration (Non-segmented; without board writing; sec)	Duration (Segmented; sec)
0	Orientation	0	50	204
1	Basics/How to make	0	426	356
2	When the relative pronoun is S	169	92	441
3	When the relative pronoun is O	0	110	499
4	Prepositions + Relative pronouns	0	722	417
5	Relative adverb: where	171	355	488
6	Relative adverb: when	145	236	293
7	Relative adverb: why	154	360	379
8	When the relational adverbs where, when, and why create [noun group]	280	525	547
9	Restrictive and Non-Restrictive Usage	162	696	529
10	some of whom/all of which	234	380	384
11	which + noun and the noun of which	227	409	374
12	Relative pronoun: what	179	298	526
13	Idiomatic expressions using the relative pronoun what	85	637	366
14	Chained relational clauses	165	311	437
	(Total amount of time)	-	5607 (including time to write board = 7578)	6240

The segmented video was divided into chapters for each of the topics in Table 1. Information on the topic and starting time can be found on the seek bar and in an area outside the video. Although the non-segmented video does not contain explicit chapters like the segmented video, its topic content and order of presentation are the same as in the segmented video. Each type of video was taken independently. The segmented video was divided into chapters on editing points, while the non-segmented video was a single shot video. The total time for the non-segmented video is longer than that for the segmented video because it includes the time for board writing. In addition, no oral explanations were given while the instructor was writing on the board. Note that the orientation clarified that the learner is free to change the playback speed and seek, especially in the segmented video.

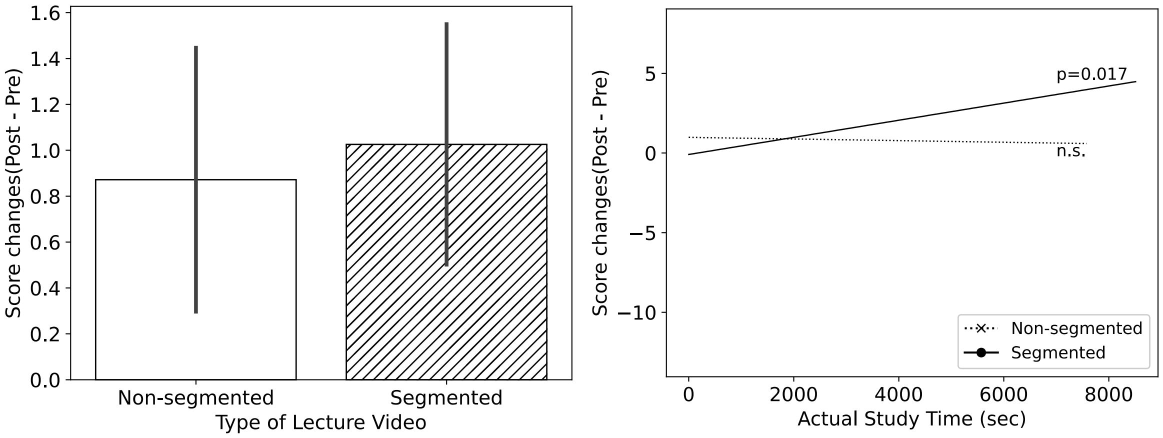
2.2 Implementation of Log Collection System

The experiment was implemented online via the experimental platform GO-E-MON (Yazawa, 2020). Video playback was implemented using the YouTube embedded player, and the JavaScript code defined on GO-E-MON was used to obtain YouTube IFrame API (Google Developers, 2021) events for video viewing logs. As a video viewing log, YouTube IFrame API records player state change events (Ended, Playing, Paused, Buffering, Cued), playback speed change events, and playback quality change events. When these events are detected, it records the player's playback status (NotStarted, Ended, Playing, Paused, Buffering, Cued), playback time on the video, playback speed, and playback quality together. Since YouTube IFrame API does not record seek operation events, they are detected by polling the player status every 100msec, checking the playback position on the video, and detecting discontinuous playback position changes.

3. RESULTS

The participants were recruited from first-year high school students. We asked the English teachers who teach the first-year students to introduce the experiment. Data were analyzed on 78 participants (41 females and 37 males) who voluntarily agreed to participate in the study based on ethical form 571-15, and completed the post-test. The segmented and non-segmented videos were randomly assigned to each participant, with each type of video being viewed by 39 participants. The participants then completed the post-test.

Figure 2 shows the increase in post-test scores relative to pre-test scores after viewing the segmented and non-segmented videos.



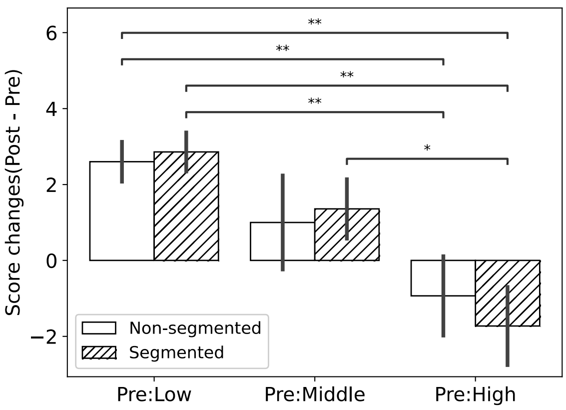
(a)Score changes per lecture video type

(b) Score changes for actual study time

Figure 2. Change in score between the segmented and non-segmented video

The average change in score per video type (a) showed an increase of 1.03 points for the segmented video and an increase of 0.87 points for the non-segmented video, indicating that the segmented video tended to improve performance, but there was no significant difference based on the t-test. However, for score improvement (b) relative to actual learning time, there was a significant correlation in the Pearson's correlation coefficient (with checking Q-Q distribution of score improvements and actual learning times, and calculating correlation coefficients) in the segmented video. The score improvement trend was observed for up to about one hour of study time for the non-segmented video, but no increase in score was observed for longer study time. A four-year study on HarvardX and MITx (Chuang, 2016) also suggested the link between actual study time and certificate rate, so the trend in the segmented video is to be expected.

In both the segmented and non-segmented videos, the score increase tends to be higher for lower pre-test scores. Pre-test scores were divided into three score ranges (low, middle, and high), and the changes in scores are shown in Figure 3.



Number of learners per Pre-test

Level	Pre-test(S)	Non-segmented	Segmented
Low	S≦3	15	14
Middle	3<S<6	9	14
High	6≦S	15	11

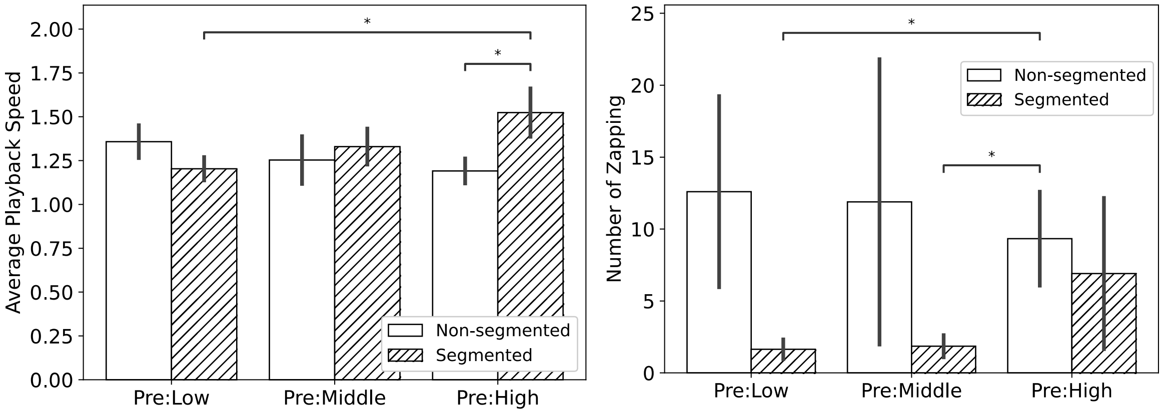
Figure 3. Differences in increasing scores by pre-test score range

The threshold for each score range was determined by sorting all participants' pre-test scores in ascending order, with the score corresponding to one-third (decimal rounded down) of the total number of participants being the upper limit of the low level and that corresponding to two-thirds (decimal rounded down) of the total number of participants being the lower limit of the high level. The change in scores by pre-test score range shows that the lower the pre-test (Pre:Low), the greater the increase in scores, and the higher the pre-test

(Pre:High), the smaller the increase. It is possible that the basic parts of the lecture videos were easy to understand and contributed to the increase in scores, but the applied parts could not be fully mastered just by watching the videos. In addition, when it comes to the high level, the average score is negative for both segmented and non-segmented videos. It is possible that the difficulty level of the pre- and post-tests was not sufficiently adjusted, and that a more accurate consideration of the increase in scores could be made by interchanging the pre- and post-tests and taking counterbalance into account.

3.1 Zapping and Playback Speed While Video Viewing

The differences in behavior between the segmented and non-segmented videos are shown in Figure 4, which presents the average video playback speed and number of zapping times for each pre-test score range.



(a)Average playback speed per pre-test score range (b)Number of zapping per pre-test score range

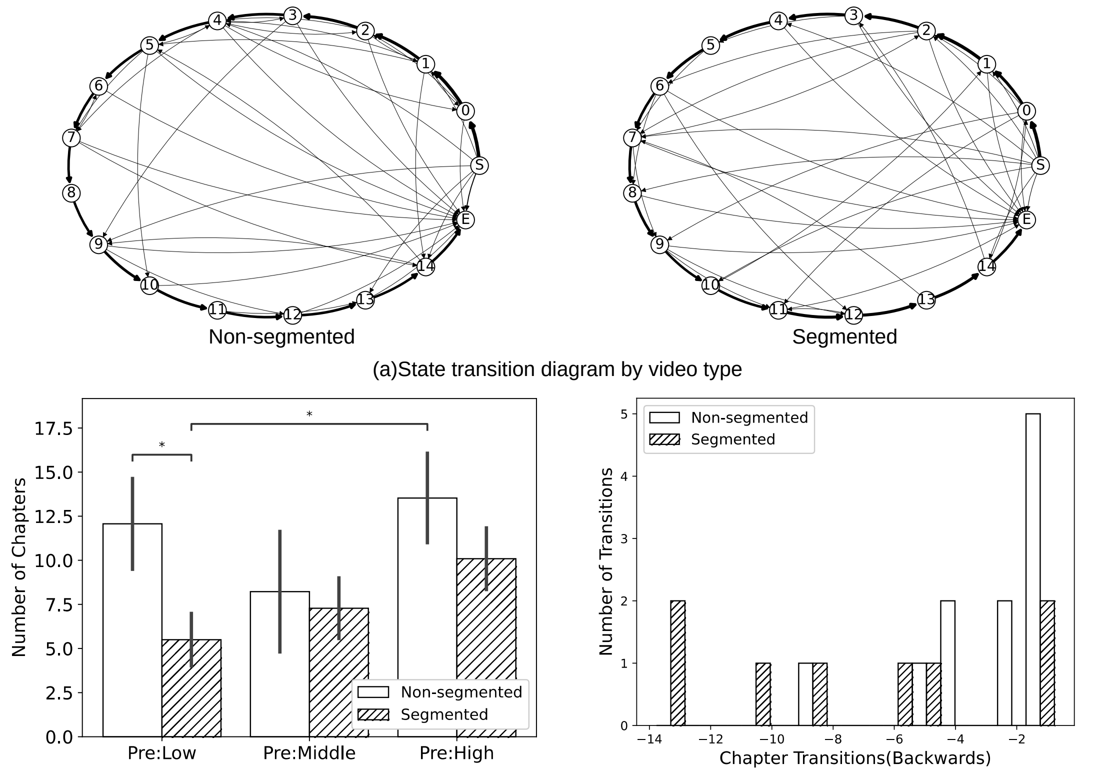
Figure 4. Relationship between Pre-test score range, zapping, and playback speed

The average playback speed is the total time watched continuously (in the video) divided by the actual total time spent on that playback. The number of zapping times is the count of the number of seek operation events that did not exceed 100 msec when immediately moving to another playback position. The average playback speed (a) shows that learners in the high-performance group of the pre-test who referred to the segmented video sped up the playback time, whereas those in the low performance group of the pre-test referred to the video at a speed close to the actual (1x) speed. Although the trend is not significant in the t-test, there is also a tendency for the low-performing group to play the non-segmented video at a faster speed and the high-performing group to play it at a speed closer to the actual speed.

The number of zapping times (b) shows that the segmented videos tended to have significantly fewer zapping times than the non-segmented videos in the low and middle pre-test score range. Thus, it is possible that many learners in the pre-test low-to-medium score range who watched the segmented video were able to use their viewing time more effectively without operating the seek bar as frequently as the non-segmented one. These results clearly show that learners behaved differently depending on the pre-test score range and the type of video they were watching.

3.2 Selection of Playback Points

The video viewing log allows a visualization of which topics in the video are referenced and in what order. Figure 5 shows a state transition diagram of the order and quantity in which topics are referenced.



(a)State transition diagram by video type

(b)Number of chapters per pre-test score range

(c)Frequency of backward chapter transitions by video type

Figure 5. State transition diagram for two videos and chapter reference and transition trends

In state transition (a), S indicates the start of playback, E indicates the end of playback, and the numbers indicate the topic number (referenced for more than 15 seconds; including board time). The thickness of the arrows is the total number of transitions for all users for each video type. The majority of users for both video types refer to the videos in order starting with the orientation. The trend (b) in the total number of topics viewed by learners in each pre-test score range indicates that the low score group in the segmented type referred to fewer chapters than the high and the low score groups in the non-segmented type. In addition, there are a small number of transitions (c) that go back to the previous topic. While many transitions in the non-segmented video return to the previous topic, transitions in the segmented video go back to a few topics earlier. By clearly indicating chapters, learners can learn even a part of a video in a short time, and those who study for a long time can refer back and review points they did not understand, which is thought to contribute to the linear effect on actual learning time.

4. DISCUSSION

This experiment showed that learners change their video viewing behavior depending on their pre-test scores, that is, their level of understanding of the topics covered by the lecture video, and the structure of the target lecture video. Although previous studies have examined learner characteristics in a video-based learning environment, such as that by Yoon (Yoon, 2021) who investigated the active and passive characteristics of learners based on their learning behaviors, few have examined learner behavior based on the structure of the video itself. This study is unique in that it showed that learners adapt their video viewing behavior according to their own abilities. The process of creating lecture videos is a hard task that requires a great deal of know-how, including experience in conducting lectures and video editing skills. However, we believe that this is an important approach in that it makes it possible to evaluate not only quantitative aspects such as the length and playback speed of existing videos, but also qualitative aspects such as composition methods, through controlled experiments.

4.1 Optimal Video Playback Speed

In this experiment, it was confirmed that the higher the pre-test score, the more likely the viewer was to watch the segmented video at a faster speed. In the study that explored the appropriate playback speed by intervention, it was shown that the low mastery level group achieved a good learning effect at 1.25 times the playback speed and the high mastery level group at 1.5 times the playback speed (Mo, 2022). This result indicates that learners themselves may be adjusting the playback speed to their own cognitive load according to their own level without external control. Conversely, the non-segmented video might show the opposite trend, which might be influenced by the writing time on the board. Assuming that the learner is also writing down notes while watching the instructor write on the board, as in an actual lecture, the cognitive load in such a case would be higher than that of just listening, and the learner may tend to slow down the playback speed. In contrast, for learners who do not engage in such behavior, board time is a time that is not cognitively loaded and can be considered to have encouraged the behavior of speeding up the playback speed change. In the future, we would like to collect behaviors other than video playback during video viewing to clarify the details of learners' adaptive behaviors to lecture videos.

4.2 Optimal Video Length

Several previous studies have concluded that the optimal length of a lecture video is a few minutes (Guo, 2014, Zhu, 2022), and increasing video engagement with short videos may be an important approach for learning services that are primarily evaluated on a course credit. On the other hand, in this experiment, the segmented videos, in which learners can easily select viewing points and methods based on their own judgment, showed score improvement in proportion to the actual time spent, which may be effective for learning services that emphasize whether the learner has completed the course or not. We believe that for learning services that emphasize mastery-based learning, preparing videos of a certain length that are systematically and appropriately divided into chapters may encourage optimal video viewing behavior according to the learner's own level of understanding and allow the learner to efficiently obtain learning results.

5. CONCLUSION

We conducted a controlled experiment with the help of a lecture specialist by creating two videos on the same topic but with different editing policies. The detailed analysis of the logs revealed that the learners adaptively changed their behavior, such as seeking and changing the playback speed of videos, according to their own abilities. This experiment demonstrated the possibility of promoting efficient learning by designing chapters based on the assumption that learners actively try to optimize their viewing behavior according to their abilities when creating lecture behaviors, and by exposing the playback control function to them.

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