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CHAPTER SEGMENTATION IN LECTURE VIDEOS PROMOTES EFFECTIVE VIEWING BEHAVIOR - BENEFITS OF UTILIZING VIDEO-PLAYING LOGS

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ABSTRACT

On-demand lecture videos play an important role in an increasingly online learning environment. However, there have not been many studies that conducted intervention experiments focusing on optimal methods of lecture video production. Most of these studies performed statistical analyses of indices such as video length, playback speed, and number of video player operations based on viewing records of existing lecture videos, such as massive open online courses. We therefore collaborated with an English lecture specialist to conduct an intervention experiment by creating two videos with the same topics, lecturers, and studios, but different editing policies. The results showed that for the video with clear chapter segmentation (but not the video without such segmentation), knowledge scores increased according to learning time. Detailed log analysis revealed that learners who viewed the lecture video with explicit chapter segmentation changed their behavior, such as seeking, changing playback speed, and skipping topics, depending on their own abilities. Based on the results, we propose that it is important for lecture video producers to organize chapters and design user interfaces based on the assumption that learners actively attempt to optimize their viewing behavior according to their abilities.

KEYWORDS

Learning Analytics, On-Demand Lecture Video, Lecture Video Production, Video Segmentation, Chapter Division

1. INTRODUCTION

On-demand lecture videos started being increasingly used as an auxiliary tool in situations where face-to-face teaching was no longer possible due to the COVID-19 pandemic (Impey and Formanek, 2021). Lectures using on-demand videos are the primary form of content for online educational services, such as massive open online courses (MOOCs) (Baturay, 2015). Since MOOCs have been reported to have high dropout rates (Onah et al., 2014), ways to improve lecture videos and achieve higher retention rates have become an important concern. One approach to improving such videos and other learning materials is by using learning analytics, which refers to the measurement, collection, analysis, and use of learner data and their situations for the purpose of understanding and optimizing the content served and its environment (Siemens and Long, 2011). It has been mentioned that most studies focused on learning analytics have analyzed learner behaviors, but only a few have addressed the improvement of learning materials (Zhu, M. et al., 2022).

One of these few studies analyzed the relationship between characteristics of lecture videos and engagement from MOOC logs (Guo et al., 2014). The researchers measured the ratio of video playback time to video length as a measure of engagement, and evaluated videos shorter than three minutes as having high engagement. However, learners were not just watching the video passively; they would actually manipulate the seek bar or change the playback speed (if allowed). These actions were more likely to occur if the videos were longer. It remained unclear how the seek bar and playback speed change functionality of the video player affects engagement and learning effectiveness. For example, in an experiment focused on learners' video viewing behavior in which the default playback speed was randomly changed, those who played a video at 1.25x speed received more certificates than those who played it at 1x speed (Lang et al., 2020). In a similar experimental intervention, a playback speed of 1.25x helped the group with low pre-test scores obtain better learning outcomes, while a speed of 1.5x helped the group with higher pre-test scores obtain better learning outcomes (Mo et al., 2022). These are interesting results, but it is unclear how these trends change with the content and style of lecture videos. 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 effectiveness if there are two video materials on the same subject. Moreover, in the early 1990s, the lack of experimental studies using interventions with controls for exogenous variables was a problem in online learning research (Phipps and Merisotis, 1999). Generally, observational studies can reveal correlations between certain factors, but it is very difficult to establish causal relationships because of the diversity of learners and materials and the many potential variables involved. Although there has been a gradual increase in the number of interventional studies over the past few years, most of them used learning dashboards as the entry point for learners to access each piece of content, and there are still few interventional studies that change the learning materials themselves, which learners are most likely to spend the most time in contact with (Tepgeç and Ifenthaler, 2022). One of the reasons for the lack of such studies is that the creation of lecture videos requires a variety of operations, including the topic structuring, the way the lecturer speaks and acts, filming and editing techniques.

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 focused on the presence or absence of clear chapter division in lecture videos as an editing policy. We analyzed how learners' behavior changed with and without chapter segmentation according to their own level of understanding, how learning outcomes changed, and what elements were necessary for an effective lecture video to be usable by learners. Learners were allowed to perform typical operations on the video player, such as using the seek bar and changing the playback speed. By acquiring and analyzing their detailed action logs, we investigated how the differences in production methods between these video materials changed users' behavior and the effectiveness of learning.

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 to evaluate their understanding of what was explained in the 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.

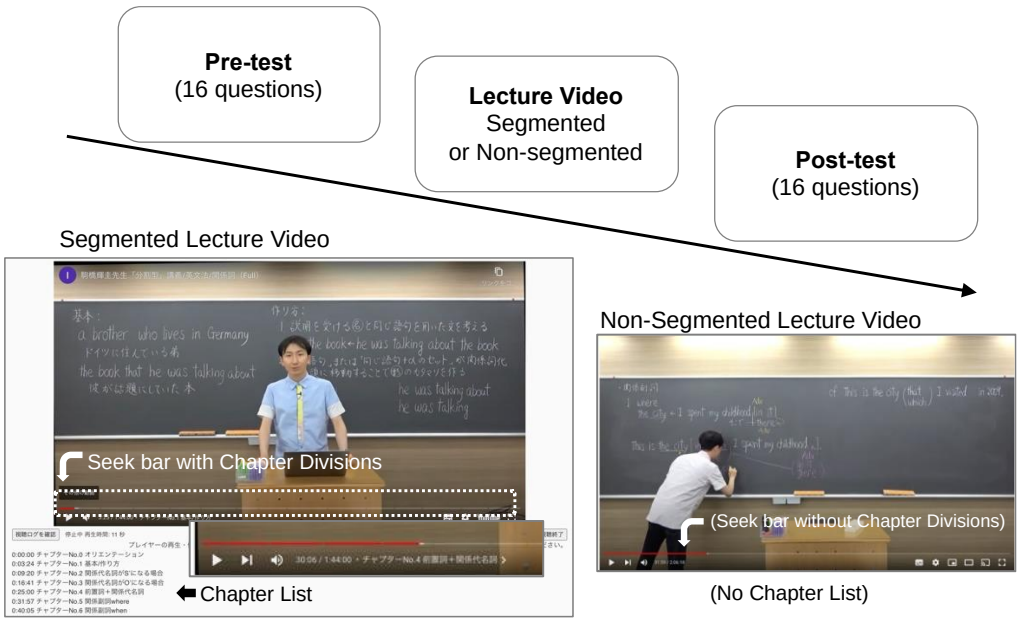


Figure 1. Task flow and prepared lecture videos

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 was divided into chapters explaining each topic, and chapter information was added and scenes

of writing on the blackboard were removed for easy handlings for learners. By contrast, the non-segmented video was a video recording of a lecture without explicit chapters and retaining scenes of writing on the blackboard. During viewing, the subjects were allowed to skip to any point in the video, change the playback speed (0.25x, 0.5x, 0.75x, Normal, 1.25x, 1.5x, 2x), and pause the video. The subjects' behaviors toward these videos were compared. Komahashi also created two types of quizzes to check comprehension: a pre- and post-test with four choices. Each test consisted of 16 questions, each test consisted of a different set of 16 questions, with each correct answer scoring as one point. There were two types of questions: one in which a sentence with one blank space was presented and the candidate was asked to select the appropriate word or phrase to fill in the blank, and the second where a sentence with multiple blank spaces and candidate words for those and the candidate had to select the right word for each blank space. Each sentences uses relative pronouns described in the video. The content of the two tests was the same for all subjects. The correct and incorrect answers and total score for each question were displayed immediately upon test completion.

2.1 Design of the Lecture Videos

Both the segmented and non-segmented lecture videos consisted of 15 topics listed in Table 1.

Table 1. List of topics with different lengths in the segmented and non-segmented videos

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 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 had a chapter for each of the topics shown in Table 1. Information on the topic and starting time could be found on the seek bar and in an area outside the video. Although the non-segmented video did not contain explicit chapters like the segmented one, its content and order of presentation were the same. Each type of video was filmed independently.

The same studio was used for both videos. The camera was fixated in front of the blackboard so that the entire blackboard could be seen on the screen, and the instructor stood in front of it, pointing or adding to the board as he offered explanations. The non-segmented video was longer than the segmented one because it included the time for board writing. In addition, no oral explanations were given while the instructor was writing on the board. The reason for including board time in the non-segmented video was to make the starting point of the next chapter less obvious. The orientation tutorial clarified that learner were free to change the playback speed and use the seek bar, especially in the segmented video.

2.2 Implementation of a Log Collection System

The experiment was implemented online via the platform GO-E-MON (Yazawa et al., 2021). GO-E-MON is a web-based experimental platform accessible on tablet devices or personal computers. Learners opened the URL assigned by the experimenter in a web browser and were able to perform the entire process of pre-test–video viewing–post-test. Video playback was available through the YouTube embedded player, and the JavaScript code defined on GO-E-MON was used to obtain YouTube IFrame API (Google Developers, n.d.) events for video viewing logs. The videos were uploaded to YouTube as unlisted, and the YouTube embedded player allowed the analysis of video playback behavior while minimizing technical considerations for load related to video streaming. 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 (not started, ended, playing, paused, buffering, cued), playback time on the video, playback speed, and playback quality together. Since YouTube IFrame API does not record seek events, they are detected by polling the player status every 100msec, checking the playback position on the video, and detecting discontinuous playback position changes. Based on the relationship between the playback position and playback speed for each polling process, the system determines whether a seek operation was performed between polling processes or whether the viewing was continuous.

3. RESULTS

The participants were recruited from among first-year high-school students who were introduced to the experiment by their English teachers. Data were analyzed for 78 participants (41 females and 37 males) who volunteered to participate and completed the pre-test. The segmented and non-segmented videos were randomly assigned to participants, with each type of video being viewed by 39 participants. The research plan approved by the Ethics Committee of the University of Tokyo (Subject No. 571-15).

Figure 2 shows the increase in post-test scores compared to pre-test ones after viewing the videos.

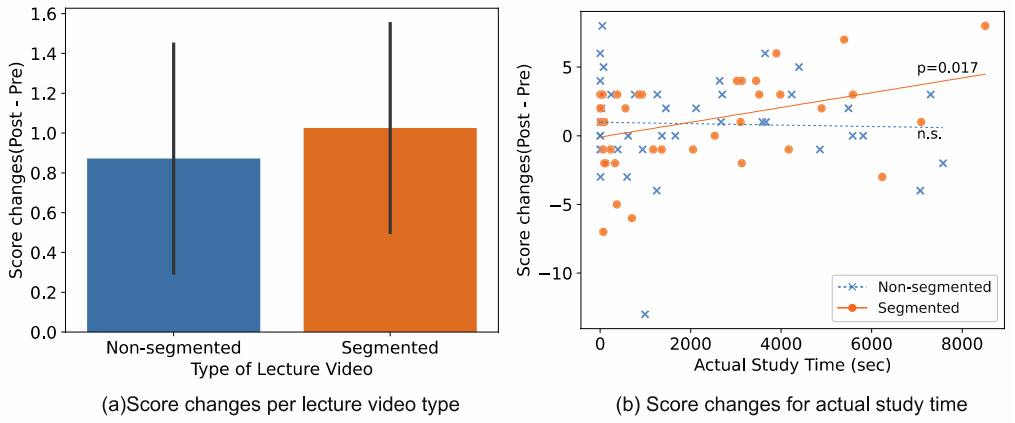
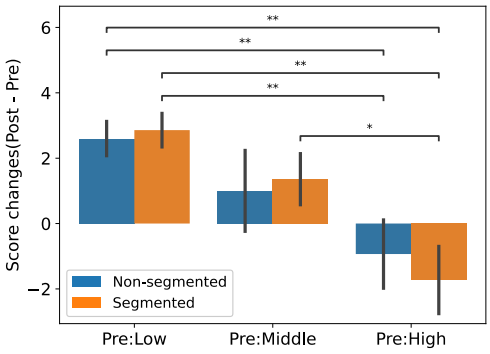


Figure 2. Change in scores between the segmented and non-segmented video

The average change in score per video type (Figure 2a) showed an increase of 1.03 points for the segmented video and of 0.87 points for the non-segmented one, indicating that the segmented video tended to perform better, but there was no significant difference based on the t-test. However, for score improvement relative to actual learning time (Figure 2b), there was a significant Pearson's correlation coefficient between actual study times and score improvements (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 approximately one hour of study time for the non-segmented video, but no increase in score was observed for a longer study time. A four-year study on online courses HarvardX and MITx (Chuang and Ho, 2016) also suggested the link between the actual study time and certification rate, so the score improvement trend was expected for the segmented video. For both videos, test scores tended to increase with study time up of about 4000 seconds, that is, up to about one hour, but for longer durations, there was a large increase in scores for the segmented video, while there was no increase for the non-segmented one. It is possible that the lack of explicit chapter segmentation prevented learners from using their learning time efficiently, leading to a decrease in scores for tests on sentences with relative pronouns.

For both videos, the increase tended to be higher on the lower pre-test scores, which were divided into three ranges (low, middle, and high). 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

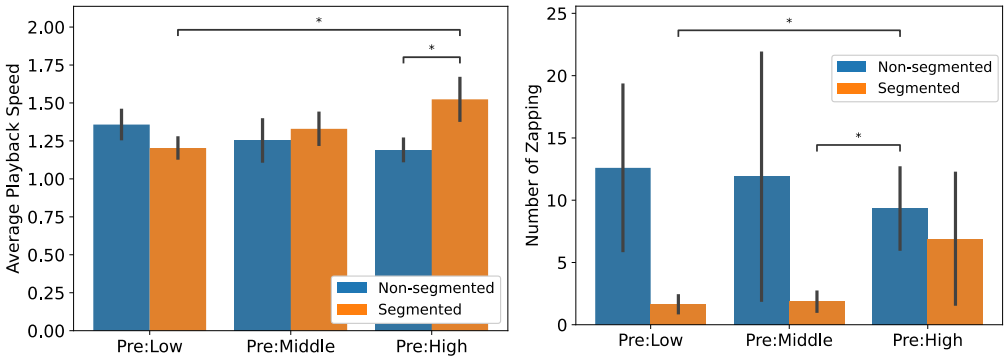
*, **: A t-test was applied to the combination of the two values and the rejection of the null hypothesis was denoted as ** for $p < 0.01$ and * for $p < 0.05$

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

The threshold for each 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 showed that the lower the scores were (Pre:Low), the greater the increase, and the higher they were (Pre:High), the smaller the increase. This tendency for the increase in scores to be smaller for learners with high prior scores than for those with low prior scores is called the ceiling effect and has been discussed in various aspects (Staus et al., 2021). The pre- and post-tests were created based on the first-year high-school English grammar content. The students who scored more than six points were considered to have potential for further score increase. However, it is possible that the students were able to gain grammatical knowledge by watching the lecture videos, but were less likely to score above a certain point because solving the questions required other forms of knowledge, such as understanding the vocabulary contained in the questions. In addition, the post-test scores of learners who achieved high pre-test scores were equal to or smaller than the pre-test scores 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. Thus, in order to assess changes in learners' abilities, it is necessary to construct an assessment with an appropriate level of difficulty that can legitimately evaluate changes in performance for all learners from low to high scoring bands, while taking into account their mastery in elements other than the experiment being conducted.

3.1 Zapping and Playback Speed While Video Viewing

The differences in behavior toward the segmented versus the non-segmented video are shown in Figure 4, which presents the average 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

*: A t-test was applied to the combination of the two types of values, and rejection of the null hypothesis ($p < 0.05$) was denoted with *

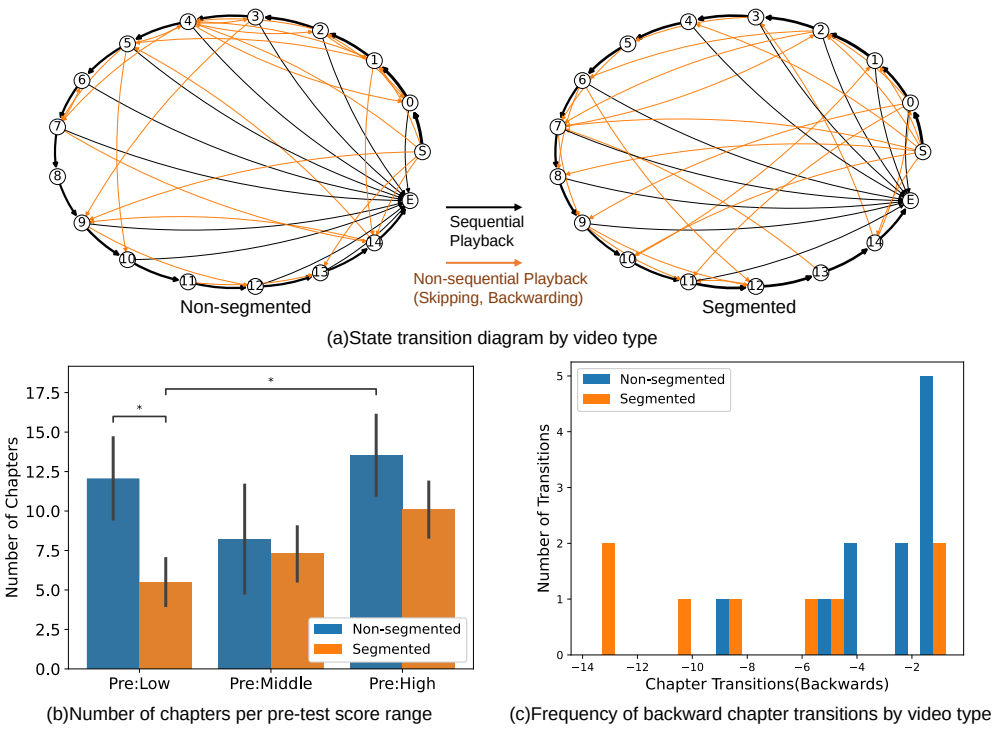
Figure 4. Relationship between pre-test score range, zapping, and playback speed

The average playback speed was 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 seek operation events that did not exceed 100 msec when immediately moving to another playback position. The average playback speed (Figure 4a) showed that learners in the high pre-test performance group who referred to the segmented video sped up the playback time, whereas those in the low pre-test performance group referred to the video at a speed close to the actual (1x) speed. Although the trend was not significant in the t-test, in the case of the segmented video, there appeared to be a tendency for the playback speed to increase along with the pre-test scores. Conversely, there was a tendency for the low-performing group to play the non-segmented video at a faster rate and for the high-performing group to play it at a speed closer to the normal one. Thus, we found differences in the tendency to alter the playback speed for each pre-test performance band between the two videos. How these differences affected the scores will be presented in the Discussion section.

The number of zapping times (Figure 4b) was significantly lower for the segmented video than the non-segmented one the low and middle pre-test score ranges. Thus, it is possible that many learners in the pre-test low-to-medium score ranges who watched the segmented video were able to use their viewing time more effectively without operating the seek bar as frequently as the viewers of the non-segmented one. Although not significantly different in the t-test, the segmented video tended to suppress zapping for all learners except those with a high pre-test score, while high-scoring learners exhibited a zapping behavior more. This can be thought of as the learner's exploration of the video content they do not understand. Conversely, for the non-segmented video viewers, there were interesting results showing that the lower the pre-test performance, the higher the zapping frequency, although the variation was greater. This may be an indication of the learner's attention span. Since no explicit topic transitions were indicated, it is possible that learners would have tried to watch the video anyway, but may have zapped when their attention lapsed. These results clearly show that learners behaved differently depending on the pre-test score range they pertained to and the type of video they were watching. This finding can be clarified by modifying the video through experimental intervention and by obtaining detailed operation logs.

3.2 Selection of Playback Points

The video viewing log allows a visualization of which topics were 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

*: A t-test was applied to the combination of the two types of values, and rejection of the null hypothesis ($p < 0.05$) was denoted with *

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

In state transition (Figure 5a), S indicates the start of playback, E indicates the end of it, 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 referred to the videos in order starting with the orientation part (black lines). Some users skipped topics or returned to topics (orange lines). The trend in the total number of topics viewed by learners in each pre-test score range (Figure 5b) 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—note that for the non-segmented video, scenes corresponding to a topic were considered as chapters. Although there is no significant difference by t-test, a tendency for the number of referenced chapters to increase as the pre-test scores increased was confirmed for segmented videos. In addition, there was a small number of transitions (Figure 5c) to the previous topic. While many transitions in the non-segmented video

returned to the previous topic, those in the segmented one went back a few topics earlier. By clearly indicating chapters, learners could assimilate 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 the actual learning time.

Another thing that can be seen from the transitions between chapters in each video type is the difference in playback from topics at the middle of the video. The non-segmented video had four types of transition destination topics from S to topics 4, 9, 13, and 14, whereas the segmented video had six types of transition destination topics from S to topics 2, 4, 7, 8, 10, and 14. In addition, while transitions from 0 (orientation) were not observed in the non-segmented video, there were two types of transitions from 0 in the segmented video (9 and 11), and many more references to the middle chapters were observed in the segmented video. By clearly showing chapters, learners were able to see how they were selecting and referring to chapters.

4. DISCUSSION

This experiment showed that differences in score changes with respect to learning time with and without chapter segmentation, and learners change their video viewing behaviors depending on their level of understanding of the topics covered by the lecture video (shown by their pre-test scores) 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 et al. (2021) who investigated the active and passive characteristics of learners based on their learning behaviors, few have examined behaviors 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 significant 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

Through this experiment, we confirmed that the higher the pre-test scores, the more likely the viewer was to watch the segmented video at a faster speed. In an experimental intervention that manipulated playback speed, the low mastery level group achieved a good learning outcome at a 1.25x playback speed while the high mastery level group at a 1.5x playback speed (Mo et al., 2022). Our experiment indicates that learners themselves may be adjusting the playback speed to their own cognitive load according to their own level of mastery without external control. Conversely, the non-segmented video might show the opposite trend, which might be influenced by the writing-on-board time. 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. By 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. In the future, we would like to collect data on behaviors other than

video playback, such as note-taking, to clarify the details of learners' adaptive behaviors to lecture videos.

Manipulations of the playback speed are common not only for lecture videos, but have also been shown to amount to 85% of the playback time on YouTube (Watson, 2022). Many playback speed changes are made from 11 p.m. local time onwards, but since this statistic does not take into account the type of video, there may be a bias between the type of content viewed at nighttime and other types of content. As for lecture videos, some may be often sped up while others may not. For example, a learner watching a video of a lecturer with a boring speaking style might make them speed up the playback. Although paper outlining guidelines for lecture videos with presentation slides (Kurzweil et al., 2020) recommends not reading the content of the slides directly, learners may speed up the video viewing rate and focus solely on the slides if they feel that the instructor is not talking about more than the slides. In order to use chapter segmentation as a control in this case, we asked professional instructors to ensure that the other elements were of sufficient quality, but new instructors may have a different tendency.

4.2 Optimal Video Length

Several previous studies have concluded that the optimal length of a lecture video is a few minutes (Guo et al., 2014; Zhu, J. et al., 2022), and increasing engagement with short videos may be an important approach for educational services that assess completion based on the time to perform exercises. However, the fact that this experiment showed score improvement in accordance with the actual viewing time and unique learning behaviors for learners of the segmented video may be important findings for educational services that emphasize comprehension of course content (i.e., scores of an assessment test for comprehension). That is, preparing videos of a certain length that are systematically and appropriately divided into chapters may encourage optimal video viewing behavior according to the learners' own level of understanding and allow them to obtain effective learning results.

Learners with lower pre-test scores watched fewer chapters in the segmentation than otherwise, yet score improvement did not differ between the two video types. Since the video playback speed was higher and zapping was less likely to occur when there was a segmentation of chapters, the result was that low-scoring learners were able to select the appropriate content for themselves and, presumably, to concentrate better on their learning. Although more references from chapters at the middle were observed in the segmented video than in the non-segmented one, the majority of all viewers referred to chapters in order from the beginning, and a more detailed examination is needed to determine whether they intentionally selected the chapters. For example, the order of topics in the videos used in this experiment was constructed based on the instructor's expertise, so it may be valuable to examine how the behavior of learners in the lower score bands would change if the order was changed.

The difference in learning outcomes between chapter-segmented videos with a certain volume and short independent videos should also be considered. Although the argument that lecture videos should be short is based on the claim that the attention span in study is 10-15 minutes, it has also been pointed out that it varies widely depending on the teacher's style (Bradbury, 2016). Viewers of the segmented video who scored low in the pre-test zapped and changed the playback speed to a lesser degree; however, if short videos are provided separately for each topic, learners must decide whether to play the next video or another one each time a video ends, and such a decision may inhibit their ability to maintain concentration and learning

motivation. In addition, since many users have been observed to return to several previous chapters in the segmented video, it may be possible to provide them with a better experience by offering chapter divisions within a single video, rather than separate videos. These issues can be investigated further through experimental interventions and detailed video playback logs; not only statistical information, but also information such as chapter transitions can be thus obtained to reveal how learners are engaging with educational videos. Such behavior would be difficult to understand based on a collective statistical analysis of various videos.

5. CONCLUSION

We conducted a controlled experiment with the help of a lecture production specialist by creating two videos on the same topic but with different editing policies. The detailed analysis of the logs revealed that the learners changed their viewing behaviors, such as seeking and changing the playback speed, 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, and by making a playback control function available. The differences in viewing behaviors we have uncovered could not have been known by simple statistics such as the number of times a video was viewed or the duration of viewing, nor could they have been known without an experimental intervention.

There are many other attributes that a lecture video can have in addition to chapter division. These elements, such as speaking techniques and topic structure, were integrated by asking a professional instructor to ensure a sufficient quality level for this experiment. However, many students would have increased the playback speed if the storytelling was boring and did not hold their attention, and they may not have taken the action of concentrating on only a few chapters if the topic was not appropriately structured. More insight into how to make lecture videos can be gained by considering interventions on these various attributes, working with the producers and recording detailed learning behaviors during the experiments.

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