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Research Article

Effects of Segmentation and Self-Explanation Designs on Cognitive Load in Instructional Videos

Hua Zheng
Charles R. Drew University of Medicine and Science, USA
ORCID: 0000-0002-3357-9878

Eulho Jung
School of Education, Johns Hopkins Univeristy, USA
ORCID: 0000-0001-7102-4243

Tong Li
Arizona State University, USA
ORCID: 0000-0002-1166-625X

Meehyun Yoon
Ewha Womans University, South Korea
ORCID: 0000-0003-3337-1660

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Abstract

This experimental study examined the effects of segmentation and self-explanation designs on cognitive load in instructional videos. Four types of instructional videos (segmentation, self-explanation, combined, and control) were created and tested by 121 undergraduate students randomly assigned to one of four research groups. The results of students' self-ratings on the cognitive load survey showed that the segmenting design produced a significantly less germane cognitive load than the two non-segmenting designs (self-explanation and control). The self-explanation design did not produce a significantly more germane load than the control design. However, students' dispositions toward segmentation and self-explanation designs were generally positive and supported the theoretical justifications reported in the literature. The findings are discussed, along with segmentation dilemmas, limitations, and future study implications.

Keywords: instructional video, multimedia learning design principle, segmentation, self-explanation, cognitive load

INTRODUCTION

Problems with Instructional Videos

Instructional videos have been increasingly used as a lesson or part of a larger lesson in education to help students learn targeted knowledge and skills (Fiorella & Mayer, 2018; Zheng et al., 2019). Instructors share educational videos created by others on online sharing platforms as part of their instruction (Chinangkulpiwat et al., 2021). The adoption of instructional videos has dramatically enriched learning materials and activities (Carmichael et al., 2018; Zheng et al., 2019). Despite the increased use of educational videos, students do not seem to apply metacognitive strategies to process dynamic multimedia information in a deep-learning manner (Kim et al., 2021; Wylie & Chi, 2014).

The absence of using metacognitive strategies while processing instructional videos leads to superficial information processing (Chi & Wylie, 2014; Fiorella & Mayer, 2018) as well as a failure to achieve higher-level learning outcomes among students, such as critiquing and evaluating the information presented in the video (Dieker et al., 2009; Lee & Kim, 2017). Merely viewing instructional videos cannot lead to a deep learning process fostering meaningful learning through videos requires effective instructional design principles for which students actively interact with visual and verbal materials during learning (Fiorella & Mayer, 2018; Kurz & Batarelo, 2010).

Research indicates that video segmentation helps with facilitating deep learning and optimizing the learning experience from instructional videos. Segmentation refers to chunking a continuous video into smaller and continuant segments, allowing students to adapt the instructional pace to their cognitive capabilities and thus sufficiently process the information of a segment before proceeding to the next piece (Biard et al., 2018). Empirical studies have been conducted to examine the effects of segmenting using instructional videos. For instance, Doolittle (2010), Doolittle et al. (2015), and Seidel (2020) found that segmentation significantly improves knowledge retention, while scholars such as Biard et al. (2018), Doolittle (2010), and Doolittle et al. (2015) identified that segmentation increases student performance in knowledge transfer.

In addition to video segmentation, prompting students to self-explain learning materials using instructional videos have also been reported to foster deep learning (Chi & Wylie, 2014; Rittle-Johnson et al., 2017). Self-explanation is defined as a meaning-making process for oneself to internalize the learning materials (Rittle-Johnson et al., 2017; Wylie & Chi, 2014). Empirical studies on multimedia instruction have shown that students who are prompted to self-explain the learning materials outperform their peers who are not prompted in terms of conceptual understanding (Chi & Wylie, 2014; Kwon et al., 2011) and transfer performance (Biard et al., 2018; Yeh et al., 2010).

On the other hand, segmentation only constructed simple learner-content interactions that allow students to click the Play/Pause button to control the video presentation pace (Evans & Gibbons, 2006; Mayer et al., 2003). Evans and Gibbons (2006) and Mayer et al. (2003) suggested the incorporation of self-explanation into multimedia instructional design, ensuring students are actively engaged in learning from the materials. Our literature review revealed that most studies have only examined the effects of incorporating either a single segmentation theory or a single self-explanation theory into an instructional video on learning performance. There is a lack of studies that have examined how design theories using video segmentations affect cognitive load (Afify, 2020). Cognitive load is considered as one of priorities when designing and producing instructional videos as cognitive load is related to students' capacity of processing video information (Sweller et al., 2011).

Examining the influence of segmentation and self-explanation on cognitive load will inform instructional designers on how to adjust the design accordingly when integrated into instructional videos (Fiorella & Mayer, 2018). According to Paas et al. (2003), learning performance is "an aspect" of cognitive load (p. 64). Any instructional design imposes cognitive load demands on students' working memory; cognitive load, in turn, affects learning performance. Consequently, cognitive load is a mediator between instructional design and learning performance (Paas et al., 2003; Sweller, 2020).

Research Purpose and Questions

Traditionally, the cognitive load has been measured in the context of learning, particularly using the traditional performance-based measures. In consideration of the impacts of cognitive load on learning, this study employs the principles of Cognitive Load Theory (Sweller, 2020) and the Cognitive Load Theory of Multimedia Learning (Mayer & Pilegard, 2014) as a primary framework (Fiorella & Mayer, 2018).

Recognizing the lack of empirical studies on the impacts of video segmentation and self-explanation on cognitive load in a learning context, this study developed and implemented four different types of instructional videos (segmenting, self-explanation, combination, and control). The development of instructional videos drew on best practices verified in empirical studies. For example, pre-determined segmentation by instructors or instructional designers may mediate learning performance more effectively than student-paced segmentation; because students, especially novices, may lack the knowledge or metacognitive skills to know when to pause the video (Biard et al., 2018; Rey et al., 2019). Self-explanation that requires recording thoughts, even when no feedback is provided, can significantly increase the perceived germane cognitive load and prevent students from passive or superficial self-explanations (Chi et al., 2018; Huk & Ludwigs, 2009). By investigating the effects of segmentation and self-explanation on cognitive load, this study contributes to the knowledge base of multimedia learning theories and cognitive theory. More importantly, the findings of this study may serve as a reference when designing courses utilizing multimedia resources.

Second, this study presents theoretical explanations that can be assumed for the effects of segmenting and self-explanation on cognitive load. Third, the theoretical effects of segmenting and self-explanation on different factors of cognitive load were investigated and verified according to the literature. Students' perspectives on their learning experiences were analyzed to further explore how segmenting and self-explanation affect the learning process. Lastly, this discusses the current study's findings, reflects on the lessons learned and limitations, and proposes future research directions. This study addressed the following research questions in the learning context using instructional videos:

1. What are the effects of segmentation and self-explanation designs on intrinsic cognitive load?
2. What are the effects of segmentation and self-explanation designs on extraneous cognitive load?
3. What are the effects of segmentation and self-explanation designs on germane cognitive load?
4. What are students' perspectives on segmentation and self-explanation designs adopted in this study?

LITERATURE REVIEW

Cognitive Load Theories on Multimedia Learning

Mayer and Pilegard (2014) proposed three assumptions in their cognitive theory of multimedia learning (CTML). First, the human information-processing system contains two separate channels for processing visual/pictorial and auditory/verbal materials. Second, each channel has a limited capacity for processing information simultaneously. Third, meaningful multimedia learning involves executing a coordinated set of cognitively active processes, which requires a substantial number of cognitive demands across the two channels.

CTML defines three types of cognitive demands: essential processing, extraneous processing, and generative processing (Mayer & Pilegard, 2014). Essential processing refers to the mental work of selecting the new information that is represented in the working memory. Extraneous processing is the mental work of processing irrelevant learning activities and materials. Generative processing is the mental work of making sense of the new information, organizing the new information into a coherent structure, and integrating the new knowledge representations with prior knowledge to solve problems. Essential and generative processing results in the creation of a meaningful learning experience. The goal of instructional design of instructional videos is to foster generative processing (Mayer & Pilegard, 2014). Each type of cognitive processing is associated with a different type of cognitive load defined in Sweller's cognitive load theory (Sweller, 2020).

Cognitive load theory is a scientific framework for identifying an optimal instructional design that efficiently utilizes an individual's limited cognitive processing capacity to acquire and apply knowledge and skills (Sweller, 2020). Cognitive load refers to the demand for working memory resources to complete a cognitive task (Paas et al., 2020). Cognitive load theory recognizes the concept of cognitive load as a crucial factor for successful instructional design (Sweller, 2020) since the construct has "a causal dimension reflecting the interactions between task and student characteristics" (Paas et al., 2003, p. 64). Paas et al. (2003) and Leppink et al. (2013) declared that cognitive load demand is an assessment dimension that reflects students' performance of a specific task. The theory differentiates three resources of cognitive load: Intrinsic cognitive load, extraneous cognitive load, and germane cognitive load (Paas et al., 2003).

Intrinsic cognitive load is associated with the inherent complexity of the learning materials and the student's existing knowledge base (Sweller, 2020). It is not easy to alter intrinsic cognitive load since the complexity of learning materials is determined based on the number and interactivity of information elements that must be processed simultaneously in the working memory (Sweller, 2020). Nonetheless, the intrinsic cognitive load can be managed by decomposing the learning materials into a series of instructional events and explicitly outlining the semantic knowledge of the learning materials (Gerjets et al., 2004; Seidel, 2020).

Extraneous cognitive load refers to the mental resources devoted to unproductive elements to learning and schemata construction or automation. Extraneous cognitive load results from inappropriate, poor instructional design, or materials that require students to process irrelevant information and interfere with learning and occupying working memory resources (Sweller, 2020). Germane cognitive load refers to the mental resources directed towards schemata construction or automation in long-term memory (Paas et al., 2003; Sweller, 2020). For example, students construct schemata when they connect new information to existing schemata in their long-term memory (Sweller, 2020). Schemata refer to the mental frameworks that bundle knowledge in an organized way and help humans integrate and predict their surroundings (Sweller, 2017). Germane cognitive load is facilitated by effective instructional design that adapts to students' needs (Sweller, 2017). Facilitating germane load is a prime goal of instruction design (Sweller, 2017). Informed by cognitive load theories on multimedia learning, this study set up design goals to prevent cognitive overload generated from the increased intrinsic and extraneous cognitive load as well as to optimize germane cognitive load.

Segmentation Effects on Cognitive Load

The rationale of segmented videos is that they allow learners to control the pacing of the presentation for fully processing the information, thus helping learners manage essential processing (or intrinsic cognitive load) (Fiorella & Mayer, 2018). The segmentation principle is consistent with the CTML's assumption of limited capacity (Fiorella & Mayer, 2018). However, the segmenting effects might be impacted by pacing design approaches (Fiorella & Mayer, 2018; Rey et al., 2019). In a study examining the effects of segmenting and pacing for novice learners, Biard et al. (2017) compared the effectiveness of three types of instructional videos (i.e., continuous, student-paced, and system-paced), and found the superiority of the system-paced segmenting effects on the procedure learning test but not on the recall test. The design of system-paced segmentation needs to highlight the salience of natural boundaries between events in a process (Biard et al., 2018; Rey et al., 2019).

On the one hand, the rationale of system-paced segmented videos is that they reduce the burden of deciding when to pause the video and helps students focus on making sense of the learning materials (Biard et al., 2018; Fiorella & Mayer, 2018). On the other hand, students can adapt the instructional pace according to their cognitive capacities, thus fully processing a segment's information before moving to the next.

The design approaches of segmentation might also produce effects on students' dispositions (Doolittle et al., 2015). In a study examining the effects of degree of segmentation on students' dispositions, Doolittle et al. (2015) chunked a 9-minute video into 1,7, 14, and 28 segments respectively, and found that increased segmentation produced a positive influence on learning outcomes (e.g., recall and application) but resulted in students' negative perceptions.

These findings confirm that segmentation helps students manage essential processing and intrinsic cognitive load. However, these studies did not investigate how segmenting impacts students' cognitive processes that offer theoretical explanations to support the segmenting effects concerning managing essential processing.

Self-Explanation Effects on Cognitive Load

The instructional goal of self-explanation is to guide learners to actively make sense of the content presented in the video by selecting, organizing, and integrating new information with existing knowledge to facilitate a highly interactive and constructive learning environment (Rittle-Johnson et al., 2017). There are different and complementary theoretical explanations that propose the effects of self-explanation on the management of essential processing and facilitation of generative processing.

First, self-explanation prompts can improve students' conceptual knowledge by focusing their attention on the particular aspects of the to-be-learned materials and identifying the structural features necessary to represent in working memory (McGinn et al., 2019; Rittle-Johnson & Loehr, 2017). Thus, self-explanation might help students manage essential processing. Second, self-explanation has contended to improve procedural knowledge, which benefits generative processing (McEldoon et al., 2013; McGinn et al., 2019). Self-explanation can also encourage students to integrate incoming new information with existing knowledge, which in turn supports and ensures schemata construction or automation, which, aids comprehension and transfer (McGinn et al., 2019; Rittle-Johnson et al., 2017; Wong et al., 2019). Furthermore, when new information conflicts with existing knowledge, students engaged in self-explanation have multiple chances to notice and fix conflicts (Durkin & Rittle-Johnson, 2012).

Use of the self-explanation method has been reported to improve students' self-efficacy in problem-solving tests (Crippen & Earl, 2007), produce higher learning performance on a transfer posttest (Mayer et al., 2020; Wong et al., 2019), and support self-regulated learning strategies (Wong et al., 2019) in different learning environments. However, these studies examined and revealed indirect self-explanation effects because many of these studies paired the self-explanation method with other instructional techniques (e.g., worked examples). Furthermore, these studies did not investigate the effects of self-explanation as a generative learning activity on cognitive load. Paas et al. (2003) and Leppink et al. (2013) declared that cognitive load demand is an assessment dimension that reflects students' performance of a specific task. To fill in the gap, this study examines how self-explanation optimizes cognitive load during learning from instructional videos with and without pairing with a segmentation method.

METHODS

Participants and Design

This study recruited 121 undergraduate students (32 males and 89 females) who completed the tasks required by the current study from the 10 sections of a face-to-face educational technology introductory course at a large public university in the southeastern United States. The participants were selected using a convenience sampling strategy, which allowed the researchers to recruit participants based on their accessibility and proximity (Creswell, 2008).

This elective course was available for the whole campus, and the participants in the current study included both education (n = 51) and non-education majors (n = 70). The participants were in different school years: 22 freshmen, 45 sophomores, 26 juniors, 25 seniors, and three fifth years. Six instructors taught the classes. Participation in this study was voluntary. Participants did not receive course credits; instead, they obtained a late pass that could be used to excuse a course absence or submit an assignment up to 48 hours after the due date without penalty.

The study was conducted in the classroom, where the course was regularly given. The first author was invited as a guest speaker to the classes and helped the instructors to administer the study. Participants were randomly assigned to one of the research groups (control, segmenting, self-explanation, and combination) to take an instructional video module.

Materials

Instructional videos

The video used in this study was entitled Singapore's 21st-Century Teaching Strategies, which was posted on YouTube by Edutopia. The video footage lasts 7 minutes and 45 seconds and covers streams of instructional activities that all focus on technology integration. The activities covered in the video include theory introductions from different stakeholders, three technology-enhanced instructional practices incorporating comments from the instructor or school's headmaster, and snapshots of faculty development activity at Ngee Ann Secondary School in Singapore. Instructional videos enrich this course by giving students more extensive learning contexts in which technology could foster meaningful learning.

Regarding the segmenting decision, the lead author played the whole video and the six video segments in two classes in a pilot study before the current study. Most of the students recommended the segmented videos, which were short with straightforward content. Furthermore, this study modeled the video design after Doolittle et al. (2015), who chunked a nine-minute historical inquiry instructional video into many segments (7, 14, and 28 segments), leading to increased learning performance. However, some students in Doolittle et al.'s study (2015) expressed negative dispositions towards the segments. This study used a web-based video editing tool called Vibby.com to chunk the whole video into six instructional events (Gerjets et al., 2004; Zacks & Swallow, 2007). Each video segment lasted 1-2 minutes and focuses on one specific scene. Vibby automatically creates a Play/Pause button for each segment to allow students to control pacing.

This study also developed seven open-ended self-explanation prompts, with one or two prompts for each segment except the last video segment, which briefly summarizes the information presented in the video. The self-explanation principle suggests that the self-explanation prompt falls along a continuum—open-ended, focused, scaffolded, resource-based, and menu-based—with specificity increasing from one extreme (open-ended) to the other extreme (menu-based) (Wylie & Chi, 2014). Open-ended, self-explanation prompts allow students to integrate information across knowledge resources and generate their explanations in the absence of any limits or expectations (Chi, 2018). Given the participants' different backgrounds and the potential of self-explanation prompts in containing their attention and thoughts (Rittle-Johnson & Loehr, 2017), this study adopted the open-ended self-explanation format so that students could critically analyze the technology integration practices using the knowledge presented in the video. This study termed self-explanation prompts as guiding questions to avoid students' confusion due to academic jargon.

Instructional modules

Four instructional video modules were developed on Google Sites. The first module was created for the control group. It used the whole video and did not provide self-explanation prompts. The second module was developed for the segmentation group. It used the six video segments and did not offer self-explanation prompts. The third module was created for the self-explanation group. It used the whole video and provided the seven self-explanation prompts. The fourth module was created for the combination group. It used the six video segments and provided the seven self-explanation prompts.

Table 1 summarizes the features of each video module. To help review the instructional design as well as to ensure content validity, this study invited an experienced instructor who taught this course for many years and two undergraduates who took this course and participated in a pilot study before the present study.

Table 1. Summary of instructional features for each instructional module

Module	Research condition	Adopted principle	Video type	Provision of self-explanation prompts
1	Control	None	A whole video	No
2	Segmentation	Segmenting	Six video segments	No
3	Self- explanation	Self-explanation	A whole video	Yes, seven prompts
4	Combination	Segmenting and self-explanation	Six video segments	Yes, seven prompts

Note sheets

This study created two types of paper-based note sheets. The sheets without prompts were provided to the two research groups—the control and segmentation groups—that did not use self-explanation. The sheets with prompts were provided to the two other research groups—the self-explanation and combined groups—that used self-explanation prompts.

Measures

Prior knowledge test

The test measured topic-specific knowledge and skills for learning the target material (i.e., meaningful technology integration that would be taught in the instructional videos). The test consisted of 10 multiple-choice, single-answer questions. The first five questions examined the conceptual knowledge of meaningful technology integration from the five aspects: (1) definition, (2) planning technology integration, (3) teachers' roles in technology integration, (4) students' role in technology integration, and (5) technology's roles in technology integration. The last five questions were for case studies that examined students' abilities to evaluate technology integration practices. Answers were scored 0 for an incorrect answer or 1 for a correct answer. Overall, a maximum of 10 points was achievable. The test was created using Qualtrics, an online survey platform. The test was developed by the lead author who had two-year teaching experience for the course. To achieve the content validity that ensured the quiz was representative of what was taught and relevant to test participants (Jenney & Campbell, 2012), this study invited an experienced instructor who had taught the course for over 13 years and two undergraduates who had taken the course before the study to review and test it; their feedback was incorporated in the test development.

Cognitive load measure

A seven-point scale of a subjective cognitive load measure was used to assess the invested amount of cognitive load during the instructional video modules. The scale was a modified version of the scale developed by Leppink et al. (2013) to examine the three factors of cognitive load. According to Leppink et al. (2013), items 1-3 addressed intrinsic cognitive load, items 4-6 addressed extraneous cognitive load, and items 7-10 addressed germane cognitive load. Each item used a seven-point Likert-type scale ("strongly disagree" to "strongly agree"). Instead of a 10-item rating scale, the adapted cognitive load scale consisted of a nine-item scale (see Appendix A). This study excluded item 4 since Cronbach's coefficient alpha was .40 for items 4-6 based on the current study participants. Cronbach's coefficient alpha value was .93 for items 1-3, .76 for items 5 and 6, and .92 for items 7-9. The overall alpha value for the nine-item scale was .75, based on the study participants.

The scale was created using Qualtrics and presented to students after viewing their instructional video modules. The use of self-rating scales is one way to measure cognitive load. It is justified by experimental findings that students can reliably assess the subjective perception of invested mental effort (Ayres, 2006; Paas et al., 2003).

Open-ended questions

This study administered open-ended questions at the end of the cognitive load survey to collect students' thoughts underlying their ratings. For the two experimental groups using the segmented video (segmenting and combination), the open question was "What are your perspectives on the video module that uses the segmented videos?" For the other two experimental groups conducting self-explanation (self-explanation and combination), the open question was "What are your perspectives on the video lesson that uses guiding questions?"

Procedure

All data collection and instructional video modules were completed on wireless laptop computers. Students were seated individually in front of laptops during a normal class period, which lasted 75 minutes. Students wore headphones when viewing the video. As 10 class sections were participating in this experiment, the experimental procedure was administered for 10 rounds. The study consisted of four main phases as follows.

Study introduction and preparation

The lead author first introduced the study and obtained students' consent. Students were then randomly assigned to one of the four research groups: (1) control (n = 33), (2) segmentation (n = 30), (3) self-explanation (n = 30), and (4) combination (n = 28). Each student was given a note sheet. The non-self-explanation groups (control and segmenting) received blank paper. The self-explanation groups (self-explanation and combination) received a notepaper on which the seven guiding questions were presented.

Administering prior knowledge test

All students viewed the whole video and completed the prior knowledge test individually. The prior knowledge test lasted for 15 minutes.

Taking video instruction

After the prior knowledge test, students were guided to the Google sites on which their instructional video module was published. The first author briefly explained the instructions for each video module and answered students' questions. Afterward, students individually viewed the video instruction. This study did not control the time spent viewing videos and taking notes. Instead, students were provided enough time (a minimum of 35 minutes before dismissing students) for completing the learning tasks required during this procedure based on the observations in a pilot study.

Assessing cognitive load efforts and reporting learning experience

Immediately following the video instruction, participants were provided the link to the cognitive load survey that included open-ended questions. The process lasted approximately 10 minutes. Finally, the first author thanked the students for their participation in the study and collected their note sheets.

Data Analysis

Preliminary analysis

All variables were preliminarily examined for accuracy of data entry and normality of distributions. The distribution was normal, and the values of skewness and kurtosis are within the acceptable range of ± 2 (George & Mallery, 2010). This study first analyzed the prior knowledge test scores using one-way analysis of variance (ANOVA) on the IBM SPSS Statistics 26 tool to examine significant differences among the four experimental groups. **Table 2** shows the descriptive statistics of the prior knowledge test scores for the four groups. The four groups did not differ significantly in terms of prior knowledge, $F (3, 117) = .629$, $p =.598$, $\eta 2 = .016$. As a result, the pretest scores were not included as a covariate in any subsequent analyses. The cognitive load ratings were analyzed using a one-way multivariate analysis of variance (MANOVA) on the SPSS. The MANOVA was conducted with a categorical variable of the group consisting of the four experimental groups as the independent variable as well as intrinsic cognitive load ratings, extraneous cognitive load ratings, and germane cognitive load ratings as the dependent variables.

Table 2. Means and standard deviations of pretest of by groups

	Control (n = 32)	Segmentation (*n* = 30)	Self-explanation (*n* = 30)	Combination (*n* = 28)
	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)
Pretest	5.48 (2.08)	5.37 (2.04)	5.63 (1.94)	6.40 (1.82)

Note: The maximum score of the pretest is 10 points.

Analyzing student responses to open-ended questions

The analysis of responses to the open-ended questions followed the procedures of open coding, axial coding, and selective coding (Strauss & Corbin, 1998). Open coding is a procedure in which similar concepts or patterns emerging from the data are identified and labeled (i.e., coded). In the current study, open coding was performed first to identify the themes regarding the effects of segmenting and self-explanation on the learning process. Axial coding relates and combs the coded themes into broader categories through constant comparison and redefinition. Lastly, selecting coding is the process of further integrating categories. The categories were brought together to capture the (positive or negative) influence of the segmenting and self-explanation designs on the learning experience in the context of the instructional video. During the coding processes, the lead author and another invited coder coded the same data independently and then met to discuss the discrepancies. The agreement was made on the initial coding sets, and categories were decided by the two coders together. After the categories were refined, the two coders discussed their analysis of each response until 100% agreement was reached.

RESULTS

Research Questions 1-3: Effects of Segmentation and Self-Explanation on Cognitive Load

Table 3 shows the descriptive statistics of the three factors of cognitive load ratings for the four experimental groups. The assumption of equality of covariance matrices was met, Box's M = 23.127, F = 1.225, p = .230. Univariate test results revealed a statistically significant effect of instructional video designs on germane load, F (3,117) = 2.896, p = .038, η2 =. 069. However, the effects of instructional video designs on intrinsic cognitive load and extraneous cognitive load were not significant: for intrinsic cognitive load, F (3,117) = 1.319, p = .271, η2 =. 033, and for extraneous load, F (3,117) = 1.805, p = .150, η2 =. 044. Therefore, the instructional video design generated significant effects on germane cognitive load among the experimental groups.

Table 3. Means and standard deviations of cognitive load by groups

	Control (*n* = 32)	Segmentation (*n* = 30)	Self-explanation (*n* = 30)	Combination (*n* = 28)
	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)
Intrinsic load[a]	9.76 (4.36)	9.57 (3.89)	9.13 (4.26)	11.29 (4.93)
Extraneous load[b]	4.52 (2.05)	5.37 (2.57)	4.00 (1.72)	4.89 (2.99)
Germane load[c]	22.42 (3.10)	20.13 (3.86)	22.43 (3.53)	21.96 (3.67)

Note: [a]the maximum score is 21 points. [b]the maximum score is 14 points. [c]the maximum score is 28 points.

Follow-up analyses were conducted for the multiple comparisons among the germane cognitive load ratings on the four types of instructional video designs to determine which of the average design germane cognitive load ratings were statistically significant. This study conducted a modified least significant difference (MLSD) test consisting of multiple comparisons performed in Microsoft Excel. The MLSD test is known as the Fisher-Hayter procedure (Hayter, 1986), which is more conservative than the LSD in inflating Type I errors but more powerful than the Tukey approach (Williams & Abdi, 2010). The MLSD uses the studentized range distribution q to calculate the critical value.

There was an unequal number of participants for each experimental group, so this study calculated the q value and Fisher-Hayter p-value for each comparison group. The results in **Table 4** show that the mean difference between the control and segmentation groups was significant, q = 3.629, F-H p-value = .03. Likewise, the mean difference between the segmentation and self-explanation groups was significant, q = 3.561, F-H p-value = .03. The mean differences between other comparison groups were not significant.

Table 4. The MLSD post-hoc test results regarding germane cognitive load ratings

Group	Group	Mean difference	*q*	F-H *p*-value
Control	Segmentation	2.29	3.629	.03*
	Self-explanation	−0.01	−0.016	1.00
	Combination	0.46	−0.716	.87
Segmentation	Self-explanation	−2.30	3.561	.03*
Self-explanation	Combination	−1.83	−2.784	.12
	Combination	0.47	0.715	.87

Note. *. $p < .05$. MLSD refers to a modified least significant difference.

Research Question 4: Students' Perspectives on Segmentation and Self-Explanation

Perspectives of the segmentation design

The analysis of participants' responses helped reveal details on how segmenting influenced their learning progress. Thirty-five students commented that the segmented videos helped them hold their attention for a longer time and concentrate on the video. A comment from one participant is illustrative:

> I like viewing segmented videos because a longer video altogether wouldn't hold my attention, and I would miss information. This way, I am given less information at a time so that I can concentrate on what the point is of that video segment.

Sixteen students expressed that segmenting allowed control of instructional pacing and thus better content understanding. The following excerpt is an example of such a comment:

> Viewing the videos as segments really helped me understand the content better. It allowed [me] to watch and process the whole video but at a rate that helped me better understand all of the topics.

Eleven students commented, as the third strength, that segmenting made learning from an instructional video easier. A participant commented as follows:

> The responses indicated that segmented videos are a great way to learn because it allows the students to give their brains a break. This makes it easier for the students to process the information.

Another noticed strength was that the pre-segmented instructional video made learning less distracting (n = 4) because students did not have to pause or go back. Segmenting made completing the learning tasks easier (i.e., taking notes; n = 7). A participant commented as follows:

> It makes it easier to understand when it is segmented and easier to take notes on specific parts.

However, some students did not like segmented videos. The reason was that segmented viewing made the learning experience distracting (n = 12). The following is a student's comment:

> I would rather view the video in one sitting. It is not that long of a video. I may understand the segmentation in a younger audience, but I am used to watching long sermons or lectures, so seven minutes broken up into 40 seconds is rather excessive and distracting.

Four students indicated that it was not necessary to segment. The following excerpt is an example from the responses:

> If the video was longer, it may have been better viewing it in segments, but because it was a short video, viewing in the segment only made it take longer to view.

Furthermore, one student commented, "I felt pressured to find something to take notes from each video because I thought the segmentation had a purpose."

Perspectives on self-explanation

The analysis of the participants' responses helped reveal how self-explanation impacted students' learning experience. Sixteen students believed that the self-explanation approach focused their attention on what to watch. For example, one student noted in the response:

> Guiding questions are helpful because they provide an idea of what to look for/focus on in the video.

Twenty-three students reported that the self-explanation approach facilitated their engagement in learning. The following excerpt is an example from one student.

> … The [guiding] questions stopped me from zoning out or getting distracted, and I have to think about what the video was showing me.

Sixteen students expressed that the self-explanation approach helped improve their understanding of the video content. A comment from one student is illustrative:

> Guiding questions are good because they help students engage with the most important topics presented in the instruction. They are helpful tools for digesting the knowledge in the material.

A small handful of students (n = 6) also reported that they were facilitated into active thinking learning. The following are two examples from the students:

> [I] liked the guided questions; [they] helped me think about and synthesize the information I was receiving through the video.

Guiding questions facilitate the awareness of specific information while eliminating any misunderstanding or the recording of any irrelevant observations

The self-explanation approach received neutral (n = 2) comments. For example, one student commented that “it doesn’t matter to me.” Furthermore, a few students (n = 4) made negative comments about the self-explanation approach, such as “maybe having less would allow the individual to focus more on the video” because “… if there are too many, they can be overwhelming and distracting.” One student expressed that “unguided instruction provides more room for independent thought.” Another student indicated that the approach slowed the learning process.

DISCUSSION

General Discussion

This study explored the effects of segmenting and self-explanation adopted in designing an instructional video on the three factors of cognitive load. The findings demonstrate that the segmenting approach did not have the expected effects of significantly reducing the intrinsic cognitive load in contrast to non-segmenting instruction (e.g., control and self-explanation). Conversely, this study noticed that the non-segmenting instructional video design produced a significantly more germane cognitive load than the segmenting design.

Nonetheless, those theoretical justifications regarding segmenting effects were revealed in the students’ reflections on their learning experience using the segmenting approach. Many students indicated that segmenting allowed them to control the instructional pacing necessary for information processing (e.g., think, reflect, digest, and integrate), take notes before moving onto the next segment, and focus their attention and thoughts on one specific thing (e.g., examples and case studies). Doing so helped ease their understanding of the content. These findings were also reported by Altinupuluk et al. (2020) who noticed that students were satisfied with learning from 11 meaningful segmented videos in open and distance learning environments. Moreover, students indicated the benefit of pre-segmenting in eliminating the burden of pausing the video. Furthermore, we noticed a large proportion of students revealed another significant theoretical justification for the segmenting effect: segmenting helped hold their attention and made them stay focused on learning for a longer time compared to the entire video. This justification has not been indicated or emphasized in the literature.

However, the current study reports that many students perceived the negative influences of segmenting. Some students expressed negative dispositions towards segmenting using wordings like “dislike,” “choppy,” “distracting,” or “slow.” Other students described a negative influence on the cognitive understanding of the background information as well as the whole idea of the presented information. These perspectives might explain the finding that the non-segmenting approaches produced more of a germane load than the segmenting approach. Doolittle et al. (2015) also revealed similar negative dispositions and comments in their study.

Regarding the self-explanation effects, the current study's findings reveal that the segmenting design did not have a significant influence on managing intrinsic cognitive load and facilitating germane cognitive load. Thus, the findings do not support the theoretical justifications claimed in the literature with regards to the self-explanation theory. However, the analysis of students' responses to the open-ended question on self-explanation design supports the theoretical justifications. Many students indicated that the self-explanation prompts helped them identify the video's main ideas and guided their attention to certain details when watching the video. These findings were consistent with the notice by Rittle-Johnson and Loehr (2017), which reported that self-explanations do not come naturally for many students and require prompts to facilitate meaningful self-explanations.

Some students commented that the self-explanation prompts facilitated their awareness of specific information while eliminating any misunderstanding or the recording of any irrelevant observations. These comments support the theoretical justifications for the self-explanation effects on improving students' conceptual knowledge (McGinn et al., 2019; Rittle-Johnson & Loehr, 2017). Moreover, many students commented that the self-explanation prompts helped them think deeply about the video's content, synthesize the information, and provoke active and critical thinking, thus facilitating learning engagement while watching the video. These descriptions support the theoretical justifications about the self-explanation approach regarding improving procedure knowledge and facilitating generative thinking. However, a few students commented on the design of self-explanation prompts by proposing the use of fewer prompts and/or self-explanation prompts to convey denser video information.

Dilemma Segmentation

The findings of the current study regarding segmenting provide insights into whether or not a short video should be segmented. Though segmenting did not produce the expected effect on germane cognitive load, the design did not significantly increase the other two factors of cognitive load. Moreover, many students who voted for segmenting reported those positive practical justifications revealed in the literature. Students do not always favor the instructional practices that most positively affect their learning (Deslauriers et al., 2019). Further, students do not always select the most appropriate study strategies when given several options (Senko & Miles, 2008). They often do not accurately identify the type and amount of help required for successful learning (Bodily et al., 2018).

Research suggests that shorter tutorials promote learning engagement, whereas learning from longer videos results in significantly decreased engagement (Guo et al., 2014). As online learning and blended learning become more prevalent, instructional videos have been increasingly adopted in the instruction of different modalities. Most instructional videos are in the form of screen captures of long lectures such as PowerPoint recordings. Thus, the current study recommends segmenting a long video into several instructional events for effective learning.

LIMITATIONS AND FUTURE DIRECTIONS

The present study adopted an experimental design to attain a high level of rigor and generalize statistical results across populations (Dousay, 2014). However, the current study should address several limitations.

The first limitation of this study is the sample size. Although this study was conducted as a part of a classroom research project involving 10 sections of a course, the pool of participants was limited by the size of the class section. The second limitation is the design of the guiding questions. Although the researchers invested much effort in this regard, we found it confounding to distinguish between different types of prompts because the literature did not provide clear definitions for each type of prompt.

The third limitation concerns the cognitive load measurement using a self-rating survey. The challenge with self-rating surveys is an issue of validity and reliability. Cognitive load is a subconscious construct. Self-report methods require participants to be introspective about their cognitive processes, and rating accuracy may be affected by participants' introspectiveness and ability to remember (Joseph, 2013).

The last limitation is the evaluation of the internal complicity of the video. No specific standards could be used to judge the aspect. The video used in this study was supposed to be a bit challenging for the participants. On the one hand, most students lacked the knowledge and skills concerning the theories and topics covered in the video. When this study was administered, the course was given for less than 3 weeks. On the other hand, many students enrolled in this course were non-educational majors. The topic and theory might not have been familiar to them.

The reported findings of the present study have important implications for the design of a meaningful instructional video. The central application is that either segmenting or self-explanation or the combined design will not generate cognitive overload for students. However, these designs produce overt, observable behaviors that indicate active learning and allow instructors to detect more easily whether or not students are appropriately engaged in learning (Chi, 2018). According to the students, each experimental design for the instructional video realized its theoretical justifications and positively affected the learning experience.

However, the segmenting operation in this study revealed controversial results. Compared with segmenting, the self-explanation design in the current study received fewer negative comments. However, the approach did not produce a statistically more germane cognitive load than the control design (the traditional approach). Considering the strengths reported by students, the current study recommends instructors and instructional designers practice segmenting and self-explanation, whether solely or in combination, in designing an instructional video to facilitate deep learning and improve learning performance. The present findings also call for future research to examine the effects of the combination of segmentation and self-explanation on cognitive load by operating fewer segments and self-explanation prompts. For measurement of student engagement and cognitive load, utilizing learning analytics to examine levels of student engagement with content may help visually quantify the data. Furthermore, although our focus was on college students, it would be useful for future research to examine how these designs apply to other age groups and types of learners (Plass & Kaplan, 2016). In addition, while our study was conducted in physical classrooms, it would be useful to determine how the designs apply in online classrooms. Research is needed to continue to deepen the evidence-based principles for the design of meaningful instructional videos.

CONCLUSIONS

The primary goal of this study was to investigate the effects of segmentation and self-explanation designs on three factors of cognitive load in instructional videos. The findings revealed that the segmentation design did not produce significantly more extraneous cognitive load but produced a significantly less germane cognitive load than the non-segmentation designs (control and self-explanation). The self-explanation design did not produce a significantly more germane cognitive load than the control design but produced significantly more germane cognitive load than the segmentation design. The combination of segmentation and self-explanation design did not produce a statistically more germane cognitive load than either the segmentation design or the self-explanation design or the control design. However, students' dispositions towards both segmentation and self-explanation designs were generally positive and supported the theoretical justifications reported in the literature.

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Correspondence: Meehyun Yoon, Ewha Womans University, South Korea. E-mail: myoon1@ewha.ac.kr

APPENDIX A

Cognitive Load Survey

Please rate how much you agree with the following statements that describe your perceived mental work while viewing the video instruction. Please be honest in marking you feel sure.

1. The topics covered in the video(s) were very complex.
2. The video (s) covered content that I perceived as very complex.
3. The video(s) covered very complex concepts and teaching practices regarding technology integration.
4. The video instruction (e.g., viewing a whole video, or viewing segmented videos, or providing guiding questions) was, in terms of learning, very ineffective.
5. The video instruction was distracting.
6. The video instruction really enhanced my understanding of the topics covered in the video.
7. The video instruction really enhanced my knowledge and understanding regarding technology integration.
8. The video instruction really enhanced my understanding of the content covered in the video.
9. The video instruction really enhanced my understanding of concepts and teaching practices regarding technology integration.