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An intervention framework for developing interactive video lectures based on video clickstream behavior: a quasi-experimental evaluation

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ABSTRACT

The purpose of this study is to develop an intervention framework based on video clickstream interactions for delivering superior user experience for video lectures. Apart from existing studies on data-driven interventions, this study focuses on video clickstream interactions to identify timely interventions for creating interactive video lectures. First, a framework was developed through an exploratory experiment, in which 29 students' clickstream behaviors were tracked on an online platform and then individual interviews were held with 17 of the students and a subject-matter expert. The framework shows how click types are transformed into interactive elements with five question types (where, why, which, how, what). It includes click types, click reasons, interventions, actions, and interactive elements. Then, a quasi-experimental study was performed with 18 students to investigate the effect of the proposed framework on the students' satisfaction and engagement. The results showed that students' satisfaction significantly increased for interactive videos created using the proposed framework when motivation was controlled. In addition, students' frequency to go back to important points decreased significantly in interactive videos, whilst students' frequency to skip unimportant points increased significantly in interactive videos. In conclusion, the proposed framework can be used to transform linear videos to interactive videos.

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KEYWORDS
Video clickstream behavior; interactive video; learning analytics; intervention framework; video lecture

1. Introduction

The increase in the number of Massive Open Online Courses, or MOOCs, and the prevalence of computers and mobile devices have recently led to learners' preference for video-based lectures (Banoor et al., 2019; Ronchetti, 2013). Low audience retention, however, is a significant problem in video lectures (Hone & El Said, 2016; Onah et al., 2014). The main reason given for low rates of student retention is the length of the video lectures (Chatti et al., 2016) and a lack of interactivity (Reyes & Trentin, 2019), which can be overcome with timely and well-designed interventions (Rienties et al., 2016) since they can positively increase performance and learner satisfaction (Zhang et al., 2006). However, existing studies have mostly proposed descriptive or predictive approaches (Belarbi et al., 2019; Jin, 2020; Mubarak et al., 2021; Sinha et al., 2014; Youssef et al., 2019) and only a limited number have taken the studies one step further by designing interventions (Gong & Liu, 2019; Şahin & Yurdugül, 2019; Zhang et al., 2020). In addition, interventions are generally designed

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using demographics, forum discussions, tasks, assessments, or online learning behaviors (Wong & Li, 2020). Descriptive approaches generally find patterns and group students or their behaviors. Prediction models are initially used to identify students at risk, then intervention strategies such as e-mails, phone calls, and instant messaging protocols are developed to increase their performance, engagement, and retention in video-based lectures (Choi et al., 2018). These strategies, however, are limited in preventing in-video dropouts as they are not real-time interventions. There are few studies focusing on real-time intervention development. Nudges based on user comments and ratings were used in a study by Dimitrova et al. (2017) to increase engagement during video lectures. However, this method is not considered applicable for learning platforms that host thousands of videos since it requires users to comment and rate at a specific point in time.

The video clickstream interactions over time can be analyzed to identify intervention points (Akçapınar & Bayazıt, 2018) considering the peak points at which students' interactions rise (Kim et al., 2014b). As a result, real-time in-video interventions can be created, which also lead to the development of interactive videos. This also supports the suggestions (Petan et al., 2014) emphasizing that interactive videos should be the main resources of MOOCs to decrease the dropout rate. The video clickstream interactions can be also tracked easily anytime by video-based learning platform without needing any extra material for each student such as mindset earphone detecting brainwave signals (Lin & Chen, 2019) to track students' viewing behaviors.

In addition, Chen et al. (2021) investigated the importance of high levels of technological engagement (LTE) on learning by comparing video-based instruction (medium LTE with linear videos) with game-based instruction (high LTE with interactive elements) and traditional instruction (low LTE with PowerPoint). And the study found that learning increased with higher LTE. In the study, game-based instruction was developed by adding interactive elements such as texts or images on the same content in linear videos as in interactive videos. This also shows that interactive videos can also provide the opportunity to gamify the videos with interactive elements. However, developing game-based instruction or interactive videos manually from the beginning is very costly, especially for MOOCs hosting already thousands of instructional videos.

Different from existing studies, this study is prescriptive and shows how to use video clickstream behaviors for designing real-time interventions during video lectures. For this purpose, the current study aims to develop a framework based on video clickstream behaviors, with two experiments based on a one-group pretest-posttest design to increase the impact of video-based lecturing. In the study, we have considered video clickstream interactions, which have become increasingly utilized in both learning analytics and educational data mining, to develop interventions for video-based lectures, which represents a first in the literature. In addition, the frameworks based on learning analytics (Bakharia et al., 2016; Fernández-Gallego et al., 2013; Greller & Drachsler, 2012; Lu et al., 2017; Scheffel, 2017; West et al., 2016) and intervention related studies in the literature are developed at macro level or do not focus on video dimension. However, the developed framework in this study focuses on video dimension at micro level. The framework is expected to guide instructors in making interactive videos based on video clickstream behaviors, and to help make students' learning both more interactive and enjoyable. The framework may also be used to improve existing courses, especially those published on MOOC platforms. Since the developed framework is also designed as a guide for changing existing linear videos into interactive videos, the redevelopment of videos for intervention will no longer be a necessity. In other words, the contribution of the current study is to propose an interactive and behavior-based solution to prevent student dropout based on an applicable intervention framework for all video-based learning platforms and to establish a baseline for the building of smart and adaptable e-learning systems.

2. Method

The current study includes two experiments based on a one-group pretest-posttest design which is one of the types of quasi-experimental study (Field & Hole, 2003). The first experiment aims to develop the framework according to students' video clickstream behaviors and to perform a preliminary analysis of the collected data. The output of the first experiment is then used as input to the second experiment. The second experiment aims to evaluate the framework, and also to answer the study's research questions. Therefore, the results of the second experiment are presented in Section 4 (Results) while the results of the first experiment are explained in Section 3.2.3.3 (Preliminary Evaluation of Framework).

Figure 1 summarizes the two experiments, complete with their aims, data collection instruments, research designs, and participants.

For both experiments, convenience sampling was used as the sampling method as the researcher had easy access to both the instructors and students from the Department of Computer Education and Instructional Technology. Each experiment includes different participants.

2.1. Research questions

Student satisfaction is considered to be a good indicator of students' learning retention and academic success (Bolliger & Martindale, 2004). Student engagement is also seen as an essential measure of learning even though it is inadequate by itself for the realization of learning goals (Cummins et al., 2016). Furthermore, student achievement is a key indicator indicating improvement in education (Nepal, 2017). Therefore, the effect of the proposed framework on students' satisfaction, video engagement, and grade scores is investigated using Research Question 1 (RQ1). Altinpulluk et al. (2020) also revealed that these are important variables for the evaluation of the effectiveness of learning. In RQ2, these measures are examined by considering students' motivation, since motivation is known to be positively related to e-learning (Harandi, 2015). Finally, RQ3 aims to investigate which behaviors change according to the proposed framework, since interventions may lead to changes in students' behaviors (Mattingly et al., 2012). These research questions evaluate the effect of the framework on students' learning by comparing the developed interactive videos with linear videos. Therefore, in this section, the term "interactive videos" is shortly used for the term "interactive videos created according to the framework".

RQ1: Are there any significant differences between linear and interactive videos in terms of students' satisfaction, video engagement, and grade scores?

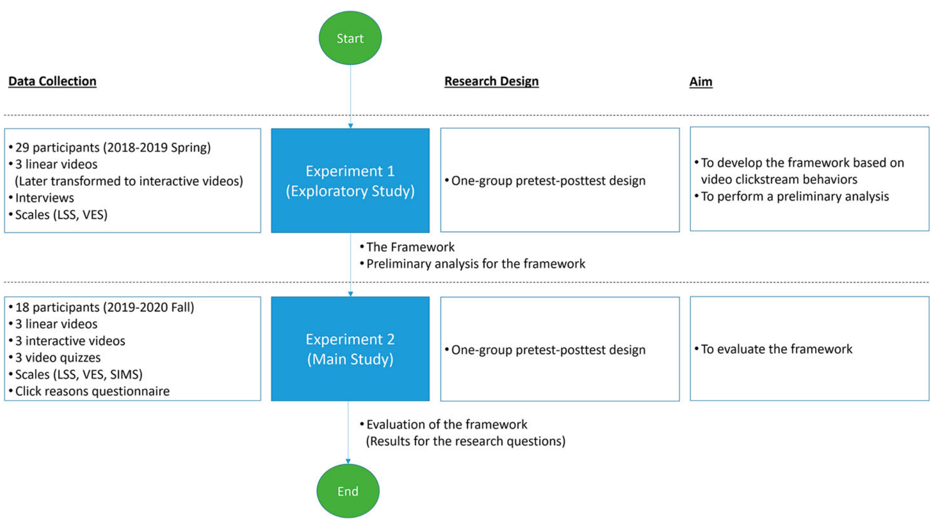


Figure 1. Overview of research methodology.

RQ2: Are there any significant differences between linear and interactive videos in terms of students' satisfaction, video engagement, and grade scores when motivation is controlled?

RQ3: How do the reasons for video clickstream behaviors change between linear and interactive videos?

2.2. Experiment 1 (exploratory study)

2.2.1. Participants

Experiment 1 was conducted within a "Principles and Methods of Instruction" course given to students (age range 20–24 years) enrolled at the Department of Computer Education and Instructional Technology (CEIT) during their fourth-semester undergraduate studies according to the CEIT curriculum at a public university in Turkey. There were a total of 29 registered students for the course.

2.2.2. Instruments

2.2.2.1. Video lectures. There were a total of three video lectures that were watched by the students in a set weekly order: (1) "Skinner: A Fresh Appraisal" (32:40 min); (2) "Piaget's Developmental Theory: An Overview" (27:06 min); and, (3) "Play: A Vygotskian Approach" (26:13 min). Each video concerns renowned educational psychologists and were each created by the same producer (Davidson Films). The duration of each video is around 30 min.

2.2.2.2. Interviews. Interviews were held with a selection of the participant students, and one subject-matter expert. The student interviews focused on "why" questions since the aim was to reveal the reasons behind the click types used. In addition, the interview made with subject-matter expert includes questions about the initial proposed framework in terms of its interpretability and accuracy of conceptual matches.

2.2.2.3. Scales. The "Learner Satisfaction Scale" (LSS) (Donkor, 2011) and "Video Engagement Scale" (VES) (Visser et al., 2016) were used to perform a preliminary analysis of Experiment 1. The LSS contains a total of seven items rated on a 4-point, Likert-type scale; whereas, the VES contains a total of 15 items rated on a 7-point, Likert-type scale. Both are validated and reliable scales. Cronbach's alpha value for LSS was found to be 0.88 in the study which was conducted for measuring its validity and reliability (Donkor, 2011). In addition, Cronbach's alpha value for VES overall was found to be 0.93 and 0.94 in two different studies (Visser et al., 2016).

2.2.3. Procedure

Experiment 1 followed three processes of the proposed framework, which were development, application, and preliminary analysis.

2.2.3.1. Development of the framework. Interventions on videos can be implemented using interactive elements that may include textual elements, images, links, or questions. Since the content of an intervention may change according to the intervention type, the actions (explanations, exercises, motivations) in the interactive elements may also differ. An experimental study was conducted in order to match click types, their reasons for usage, corresponding interventions, related actions, and interactive elements with each other.

The study includes the seven steps and each are explained respectively:

Step 1: Students watched three linear videos in a set order in a computer laboratory over a 3-week period (one video per week).

An online platform, developed to track students' video clickstream interactions including the use of the play, pause, forward, backward, volume up, volume down, mute, unmute, full screen on, and full screen off functions, was used. After watching each video, the students took a mini-quiz and then completed the LSS and VES scale instruments.

Step 2: Students' video clickstream behaviors were analyzed.

We discovered that the students did not generally perform click interactions beyond what may be considered the basics (i.e. play, pause, forward, and backward). Therefore, this part of the analysis focused particularly on the three significant interaction types (pause, forward, and backward). For each video, line graphs and box plots were created for each interaction type so as to reveal the peak points. Figure 2 presents an illustrated example of the "backward" interaction counts recorded for the video about Skinner.

Step 3: Interviews were conducted with 17 students about their video clickstream behaviors.

Prior to the interviews, graphs were prepared for the three most significant click types of pause, backward, and forward for each student. These graphs were shown to each student and they were then asked for their reasons behind the areas of high-click intensity.

Step 4: Student interview contents were analyzed using content analysis strategy to reveal the reasons given for each type of click.

Content analysis aims to extract significant categories or themes from text or speech (Zhang & Wildemuth, 2005). The analysis results are presented in Table 1.

Step 5: Initial framework (Version 1) was developed based on interview results and literature review.

Whilst developing the framework, the researchers aimed at guiding educators and academicians as to where to place elements in videos. In the literature, there are four important interactive elements noted: question, text, image, and link (Bakla, 2017; Kleftodimos & Evangelidis, 2016; Magdin et al., 2011).

As Geller (2005) and also Şahin (2018) stated, there are three types of intervention; instructional, supportive, and motivational.

The initial framework presented in Figure 3 was created according to the interview results and the published literature.

The motivation behind the framework is that matching suitable interactivity techniques with different video clickstream behaviors may be helpful to transform existing linear videos into interactive videos.

Step 6: Interview was conducted with subject-matter expert having 9 years' instructional technology experience which included MOOCs.

Each element of the framework was discussed with the subject-matter expert, and the interview helped to improve intervention type determination for each click reason.

Step 7: Framework was revised as Version 2.

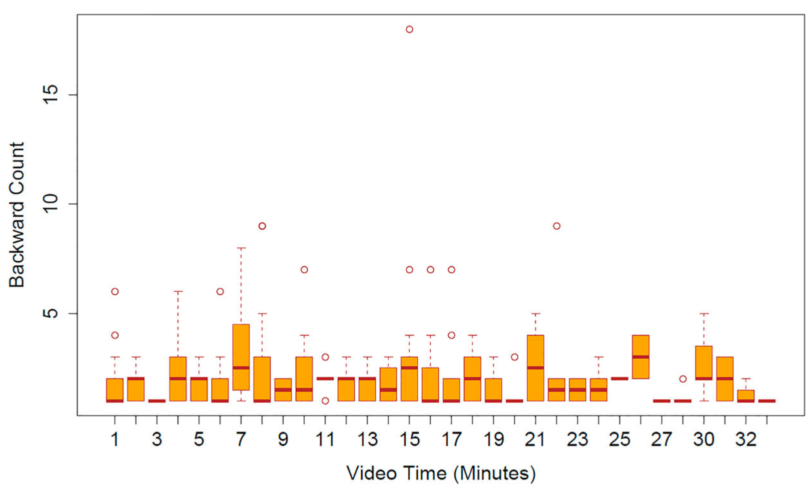


Figure 2. Box plot for backward (Skinner).

Table 1. Reasons of clickstream behaviors.

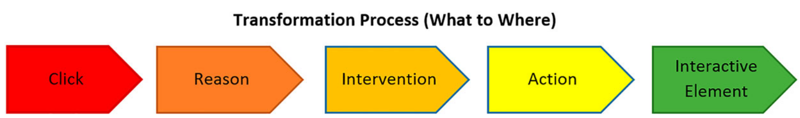
Click type	Reason
Pause	Notetaking
Backward	Important points
	Language issues
	Not understanding
	Losing concentration
Forward	Unimportant points
	Finishing quickly
	Skimming

Click priority was added in Version 2 to clarify where different click types were performed at the same points of a video lecture. “click priority” means:

- Forward may support Backward
- Backward may support Pause

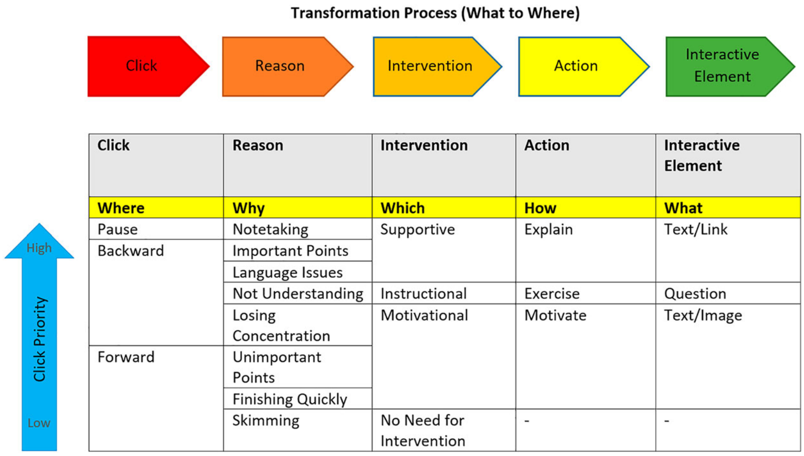
Therefore, where “pause” followed by “backward” were clicked at the same point in a video, “notetaking” was taken as the reason for the clicks having been made by the user. Also, where “backward” was clicked followed by “forward” at the same point in a video, one of the reasons pertaining to “backward” will be taken as the reason (see Figure 4).

2.2.3.2. Application of framework. First, interactive videos were developed based on the framework using h5p. Interactive elements (question, text, image and link) were added to linear videos according to the framework. Therefore, interactive elements in the framework are the interventions in this study. The number of interventions, which were determined according to the peak points in the linear videos, was found to be 11, 16, and 14, respectively, in three interactive videos. Next, the same students that participated in the development phase watched the interactive videos one month later. Figure 5 shows example interventions:



Click	Reason	Intervention	Action	Interactive Element
Where	**Why**	**Which**	**How**	**What**
Pause	Notetaking	Supportive	Explain	Text/Link
Backward	Not Understanding			
	Important Points	Instructional	Exercise	Question
	Language Proficiency			
	Speaker’s Accent			
	Losing Concentration	Motivational	Motivate	Text/Image
Forward	Unimportant Points			
	Finishing Quickly			
	Skimming	Instructional	Exercise	Question

Figure 3. Initial version of the framework.



Click	Reason	Intervention	Action	Interactive Element
Where	**Why**	**Which**	**How**	**What**
Pause	Notetaking	Supportive	Explain	Text/Link
Backward	Important Points			
	Language Issues			
	Not Understanding	Instructional	Exercise	Question
	Losing Concentration	Motivational	Motivate	Text/Image
Forward	Unimportant Points			
	Finishing Quickly			
	Skimming	No Need for Intervention	-	-

Figure 4. Final version of the framework.

2.2.3.3. Preliminary evaluation of framework. Whilst watching the interactive videos, the students evaluated each intervention in terms of its timing and content, as well as the effect of the framework in terms of their engagement and satisfaction. In this respect, timing refers to the intervention having been presented at the perceived correct time; whereas, content refers to the suitability of the intervention with the video content at that moment. Wachtler et al. (2016) emphasized the importance of evaluating the timing and content of interventions in interactive videos. For this, two questions are presented in the survey (one for timing and one for content). The participating students provided an answer for each question for each intervention, between "1" (Very bad) to "5" (Very good). The LSS and VES scores from the interactive videos were also compared with those from the linear videos.

The results showed that the timing and content for the interventions were evaluated by the students as being good (see Table 2). However, the interventions did not elicit a statistically significant change in the students' satisfaction or their engagement to the video lectures. The reason could be the framework may not work the same for all students, and as such perceived as being of more help for those who feel in need of interventions. Therefore, it may be more prudent to investigate the effect of additional variables, especially motivation.

In the first experiment, watching the same videos before and after treatments by the participants may have affected the results. Therefore, it was decided to conduct a second experiment in which different videos before and after treatments were watched.

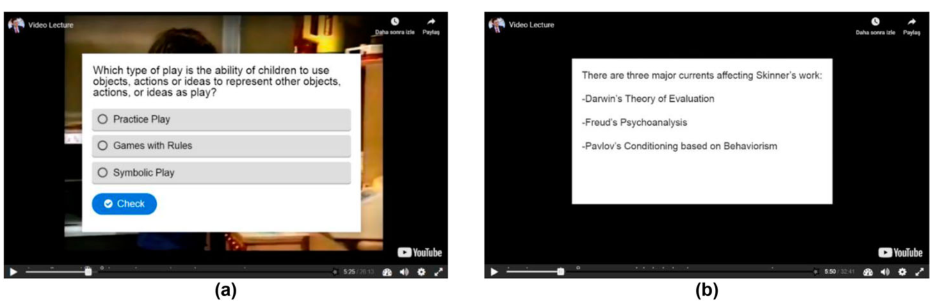


Figure 5. Example interventions with interactive elements. (a) Question, (b) text.

Table 2. Intervention results.

Video	Type	*n* (students)*	Timing	Content	Mean
1	Motivational	25	3.86	3.56	3.71
	Instructional	25	4.07	4.39	4.23
	Supportive	25	4.42	4.53	4.47
2	Motivational	25	3.81	3.71	3.76
	Instructional	25	4.40	4.48	4.44
	Supportive	25	4.33	4.32	4.33
3	Motivational	22	3.86	3.71	3.79
	Instructional	22	4.35	4.38	4.36
	Supportive	22	4.41	4.47	4.44

*25 of the students watched the first and second videos and 22 of the students watched the third video after interventions were added.

2.3. Experiment 2 (main study)

2.3.1. Participants

The participants in the main experiment were students (age range 20–24 years) registered to an "Instructional Principles and Methods" course during the 2019/2020 Fall semester. There were a total of 22 students registered for the course; however, two subsequently dropped the course and two of the remaining course attendees did not watch both linear and interactive videos. In total, 18 of the students watched both the linear and interactive videos.

2.3.2. Instruments

2.3.2.1. Video lectures. A total of six video lectures (three linear videos and three interactive videos) were watched by the students during their course. The interactive videos were those developed during the first experiment based on the framework. In the second experiment, the linear videos or interactive videos were different from each other and none of them was watched by the participants before. The three linear videos were; (1) "Maria Montessori: Her Life and Legacy" (35:10 min), (2) "Erik H. Erikson: A Life's Work" (30:42 min), and (3) "John Dewey: His Life and Work" (29:55 min), whilst the three interactive videos were; (4) "Skinner: A Fresh Appraisal" (32:40 min), (5) "Piaget's Developmental Theory: An Overview" (27:06 min), and (6) "Play: A Vygotskian Approach" (26:13 min). Videos which are different from the ones in the first experiment were also set to be around 30 min in this experiment. They are also published by the same producer (Davidson Films).

2.3.2.2. Scales. In addition to the Satisfaction (LSS) and Engagement (VES) scales used in the exploratory experiment, intrinsic motivation subscale of the Situational Motivation Scale (SIMS) (Guay et al., 2000) was applied in this main experiment. The effect of the framework on the students' satisfaction, engagement, and academic grades, after taking motivation into account, were investigated using the intrinsic motivation subscale, which contains four items rated on a 7-point, Likert-type scale instrument. Reliability and validity of the subscale were also ensured based on the results of the study of Guay et al. (2000).

2.3.2.3. Questionnaire. Click Reason Questionnaire was used to measure the impact of each intervention type and investigate changes in the students' intervention needs. It was created from the reasons that need intervention in the framework, and contains seven items rated on a 5-point, Likert-type scale. Figure 6 shows the questionnaire:

2.3.2.4. Video quizzes. Six video quizzes were presented to the participant students, with one quiz following each video lecture, which consisted of eight or nine content-related multiple-choice or true/false questions.

During the video lecture,	1 (Never)	2 (Sometimes)	3 (Often)	4 (Usually)	5 (Always)
I took notes.					
I lost concentration.					
I did not understand the content.					
I faced language issues.					
I went back to important points.					
I skipped unimportant points.					
I wanted to finish quickly.					

Figure 6. Click reasons questionnaire (created from the proposed framework).

2.3.3. Procedure

The experiment lasted for a total of 6 weeks. During the first 3-week period, the linear videos were used, whilst during the second 3-week period, the interactive videos were presented:

During the first 3-week period, each week the students:

(1) Watched a linear video at home.
(2) Completed the scales at home (pretest).
(3) Took part in a classroom-based quiz (pretest).

During the second 3-week period, each week the students:

(4) Watched an interactive video at home.
(5) Completed the scales at home (posttest).
(6) Took part in a classroom-based quiz (posttest).

There were a total of 97 observations (44 observations from linear videos and 53 observations from interactive videos) collected from 18 students as some of the students did not watch all video lectures. As mentioned in Section 3.2.3.2, the effect of framework was investigated with interactive videos which were transformed from linear videos by adding interactive elements (or interventions in this study).

3. Results

3.1. Results for RQ1

The first research question consists of three sub questions:

> RQ1.1: Is there a significant difference between the linear and interactive videos in terms of students' satisfaction?
>
> RQ1.2: Is there a significant difference between the linear and interactive videos in terms of students' engagement?
>
> RQ1.3: Is there a significant difference between the linear and interactive videos in terms of students' grades?

Paired sample *t*-test (as subjects are independent and pairs are from the same participants) was performed to compare each related variable (satisfaction, engagement, or grade) between the linear videos and the interactive videos since the assumptions were met for paired sample *t*-test. The average scores for the linear and interactive videos were used to perform the analysis. Since there were 18 students who watched both linear and interactive videos in the main study, their data was used in the analysis to answer research questions.

Table 3 presents the results for RQ1. As can be seen, the results for the "satisfaction" variable shows that no significant difference was found to exist between the linear ($M = 2.54$, SD = 0.69) and interactive videos ($M = 2.50$, SD = 0.50) in terms of the students' satisfaction ($t(17) = 0.281$, $p > .05$). Similarly, for the "engagement" variable, no significant difference was found to exist between the linear ($M = 3.40$, SD = 0.99) and interactive videos ($M = 3.00$, SD = 0.50) in terms of the students' engagement ($t(17) = 1.94$, $p > .05$). Finally, the results for the "grade" variable showed no significant difference having been found to exist between the linear ($M = 84.56$, SD = 13.20) and interactive videos ($M = 84.38$, SD = 7.50) in terms of the students' grades ($t(17) = 0.066$, $p > .05$).

As a result, the proposed framework did not elicit significant changes to the students' engagement, satisfaction, or grade scores.

3.2. Results for RQ2

One of the outputs from the first experiment was to examine the students' motivation as a covariate. Therefore, this second research question aimed to investigate the effect of the proposed framework on the students' satisfaction, their engagement, and their grade scores where the students' motivation was controlled. In addition, this research question presents a good opportunity to see the importance of motivation as well as to explore the impact of the framework. The second research question consists of three sub-questions:

> RQ2.1: Is there a significant difference between the linear and interactive videos in terms of the students' satisfaction score where motivation was controlled?
>
> RQ2.2: Is there a significant difference between the linear and interactive videos in terms of the students' engagement score where motivation was controlled?
>
> RQ2.3: Is there a significant difference between the linear and interactive videos in terms of the students' grade score where motivation was controlled?

As long as assumptions (Li & Chen, 2019, p. 201) were met, analysis of covariance (ANCOVA) was used where motivation was selected as a covariate, as well as user identifier was selected as a random factor since users have more than one observation. For those not meeting the assumptions, Quade (1967)'s ANCOVA was used. Then, the main effect of video type (linear or interactive) based on estimated marginal means was compared for each variable. Table 4 presents the comparison results for each variable when motivation was controlled..

For satisfaction and engagement, parametric ANCOVA was performed as assumptions were met. However, Quade's ANCOVA was used for grade since homogeneity of variance was violated for grade. Table 4 presents the comparison results for each variable when motivation was controlled. The results for the "satisfaction" variable showed that there was a significant difference found to exist between the linear ($M = 2.43$, SD = 0.06) and interactive videos ($M = 2.59$, SD = 0.06) in terms of the students' satisfaction when motivation was controlled ($p = .039$, $< .05$). Although the effect size is small, the difference between adjusted mean scores is noticeable. However, the results for the "engagement" variable showed no significant difference having been found to

Table 3. Comparison of mean scores for satisfaction, engagement and satisfaction.

Variable	Video type	*n* (students)*	*M*	SD	*df*	*t*	Cohen's *d*	*p*
Satisfaction	Linear	18	2.54	0.69	17	.281	.07	.782
	Interactive	18	2.50	0.50				
Engagement	Linear	18	3.40	0.99	17	1.985	.46	.070
	Interactive	18	3.00	0.50				
Grade	Linear	18	84.56	13.20	17	0.066	.02	.948
	Interactive	18	84.38	7.50				

*18 students watched both linear and interactive videos in the main study.

Table 4. Comparison of mean scores for satisfaction, engagement and satisfaction when motivation is controlled.

Variable	Video type	*n* (obs.)*	Mean	SD	Mean (adjusted)	SE	*F*	η^2	*p* (adjusted)
Satisfaction	Linear	44	2.54	0.79	2.43	0.06	4.440	.069	$p = .039$
	Interactive	53	2.52	0.66	2.59	0.05			
Engagement	Linear	44	3.41	1.24	3.19	0.11	0.076	.001	$p = .784$
	Interactive	53	3.00	1.19	3.15	0.10			
Grade**	Linear	44	85.40	18.66	−2.20	2.31	1.304	.021	$p = .258$
	Interactive	53	84.62	14.35	1.31	2.02			

*There were a total of 97 observations (44 from linear videos and 53 from interactive videos) obtained from 18 students.
**Rank was used for Quade's ANCOVA.

exist between the linear ($M = 3.19$, SD = 0.11) and interactive videos ($M = 3.15$, SD = 0.10) in terms of the students' engagement when motivation was controlled ($p > .05$). Similarly, the results for the "grade" variable showed no significant difference was found to exist between the linear ($M = -2.20$, SD = 2.31) and interactive videos ($M = 1.31$, SD = 2.02) in terms of the students' grades when motivation was controlled ($p > .05$).

The results show that the proposed framework was found to be effective in terms of the participant students' satisfaction when motivation was controlled; whereas it did not elicit a significant effect on either the students' engagement or grade scores when motivation was controlled.

3.3. Results for RQ3

The aim of interventions is to elicit a change from undesirable to desirable behaviors. Therefore, the current research also investigated any changes in the reasons for watching behaviors based on the interventions offered in the proposed framework. Since there were seven reasons found to require intervention in the proposed framework, this third research question consists of seven sub-questions:

> RQ3.1: Is there a significant difference in the frequency of notetaking between the linear and interactive videos?
>
> RQ3.2: Is there a significant difference in the frequency of concentration loss between the linear and interactive videos?
>
> RQ3.3: Is there a significant difference in the frequency of lack of understanding the content between the linear and interactive videos?
>
> RQ3.4: Is there a significant difference in the frequency of language issues faced between the linear and interactive videos?
>
> RQ3.5: Is there a significant difference in the frequency of returning to view important points between the linear and interactive videos?
>
> RQ3.6: Is there a significant difference in the frequency of skipping unimportant points between the linear and interactive videos?
>
> RQ3.7: Is there a significant difference in the frequency of wanting to finish quickly between the linear and interactive videos?

Paired sample *t*-test was employed for those meeting assumptions to answer sub-questions of RQ3. Wilcoxon signed-rank test was applied for RQ3.4. as having not met assumptions of paired sample *t*-test after omitting outliers. The average scores for the linear and interactive videos were then used for the analysis. *p*-values were also adjusted according to Benjamini–Hochberg (1995) procedure to perform correction for multiple comparisons. Table 5 presents the results for each of the seven sub-questions of RQ3:

In Table 5, significant differences were found to exist for two out of the seven click reasons ("Going Back to Important Points" and "Skipping Unimportant Points"). First, a significant difference was found to exist between the linear ($M = 2.97$, SD = 1.13) and interactive videos ($M = 2.57$, SD =

Table 5. Comparison of reasons between linear and interactive videos.

Reason	Video type	*n* (students)	*M*	SD	*df*	*t*	*p* (adjusted)
Notetaking	Linear	17*	2.76	1.42	16	.389	.718
	Interactive	17*	2.71	1.45			
Losing concentration	Linear	18	2.71	0.95	17	.553	.718
	Interactive	18	2.61	0.85			
Lack of understanding the content	Linear	18	1.83	0.83	17	−.408	.718
	Interactive	18	1.90	0.79			
Going back to important points	Linear	18	2.97	1.13	17	2.742	.049
	Interactive	18	2.57	1.08			
Skipping unimportant points	Linear	18	1.54	0.69	17	−3.292	.028
	Interactive	18	2.10	0.82			
Wanting to finish quickly	Linear	18	3.10	1.27	17	−.367	.718
	Interactive	18	3.17	1.12			
Reason	Video type	*n* (students)	*M*	SD		*Z****	*p* (adjusted)
Facing language issues	Linear	16**	1.93	0.92		−1.615	.247
	Interactive	16**	1.78	0.88			

*One outlier for taking notes was omitted.
**Two outliers for facing language issues were omitted.
***Wilcoxon signed-rank test was used for facing language issues since it did not meet assumptions for *t*-test.

1.08) in terms of the students' frequency of going back to view important points, $t(17) = 2.74$, $p < .05$. Second, a significant difference was found to exist between the linear ($M = 1.54$, SD = 0.69) and interactive videos ($M = 2.10$, SD = 0.82) in terms of the students' frequency of skipping unimportant points, $t(17) = -3.29$, $p < .05$.

In addition, the students were shown to have taken notes more ($M_{\text{linear}} = 2.76 > M_{\text{interactive}} = 2.71$), lost concentration more ($M_{\text{linear}} = 2.71 > M_{\text{interactive}} = 2.61$), and faced language issues more ($M_{\text{linear}} = 1.93 > M_{\text{interactive}} = 1.78$) in the linear videos than in the interactive videos, even where the results were found to be non-significant.

4. Discussion and conclusion

In the current study, the students' satisfaction increased significantly for the interactive videos created based on the proposed framework when motivation was controlled. In addition, the students' frequency of going back to view important points decreased significantly for the interactive videos, whereas the students' frequency to skip unimportant points increased significantly for the interactive videos. These findings also show that the framework can support both signaling and weeding, which are two known design principles of cognitive theory for multimedia learning used to reduce cognitive load (Mayer & Moreno, 2003). Both of these principles are considered to be important practices that should be focused upon in the creation of effective educational videos (Brame, 2016). Therefore, the proposed framework may be used to help decrease students' cognitive load; that is, students may acquire the same level of information with a reduced amount of effort. In addition, the current study has shown that students' motivation can play a role in their academic success. This finding proves that motivation is an essential factor in student learning (Järvelä, 2001), as where motivation was controlled, students' satisfaction was shown to increase significantly in accordance with the proposed framework. Even where motivation was not controlled, it was seen that linear videos could be made interactive without causing any decrease in the students' achievement (grade) based on the proposed framework. In terms of student engagement, adding interactive elements to peak points is considered to be a good option so as not to lose engagement with the student in the long term, but is insufficient to increase engagement. This finding supports the literature in that interventions should be added to points where engagement is seen to be low rather than where it is high (Xiao, 2017). Therefore, the current study's results appear to be consistent with existing studies that have examined the effect of embedded interactive questioning (Marshall, 2019). This study has also highlighted the importance of location in terms of interactive elements. Accordingly, this study suggests investigating dip points where current interaction is considered to be low, as also stated by Kim et al. (2014a).

The results in this study showed the framework is helpful to a certain degree on long instructional videos and this can be associated with learning design activities (Rienties & Toetenel, 2015). While using in-video interventions when creating interactive videos helps contribute to the learning design, especially in terms of interactive, experiential, and assessment activities in video lectures, it does not decrease the number of assimilative activities (e.g. reading, watching, listening, etc.). Holmes et al. (2019) showed the positive effect of high number of assessment and interactive activities and negative effect of high number of assimilative activities on students' learning performance and satisfaction. Therefore, the effect of the framework on learning is likely to increase in short instructional videos since the rate of assimilative activities naturally decreases with short videos.

In conclusion, the study proposes an intervention framework based on video clickstream interactions to identify real-time interventions for the development of interactive video lectures. The framework can be used to decrease students' cognitive load on online courses, as well as it can form a basis for inventing intelligent and adaptive e-learning systems. Finally, linear videos can be transformed to interactive videos with the framework.

4.1. Limitations and future work

Even though the current study provides valuable insights into a framework based on the video clickstream behaviors of students, it has limitations.

First, the study included only a small number of participants. As this is an experimental study with repeated measures, each participant needed to spend significant time to complete the experiment. With a limited number of available participants, the sample could not have been assigned to two different groups, such as with a control group and an experimental group. Therefore, a quasi-experimental study was conducted as the main study with a pretest-posttest design. Second, in the development phase of the framework, the interview was made with a single subject-matter expert since reaching more subject-matter expert on both MOOCs and instructional technology was not possible. However, the subject-matter expert has also a PhD in MOOCs from the department of Computer Education and Instructional Technology and enough experience as mentioned in Section 2.2.3.1.

As a future study, we are planning to perform additional experimental research to assess the effect of the proposed framework on different courses. We also believe that the framework will help to decrease academic achievement gap between students. Therefore, additional research is also planned to measure the effect of the proposed framework on the achievement gap between students.

Ethics statement

This research was granted with approval from Middle East Technical University's Ethics Committee (Protocol No: 189-ODTÜ-2019) and the consent forms were collected from the participants.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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