International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
Volume 25, Number 2

May – 2024

Decoding Video Logs: Unveiling Student Engagement Patterns in Lecture Capture Videos

Gökhan Akçapınar[1], Erkan Er[2], and Alper Bayazıt[3]
[1]Department of Computer Education and Instructional Technology, Hacettepe University; [2]Department of Computer Education and Instructional Technology, Middle East Technical University; [3]Department of Medical Education and Informatics, Ankara University

Abstract

Lecture capture videos, a popular type of instructional content used by instructors to share course recordings online, play a significant role in educational settings. Compared to other educational videos, these recordings require minimal time and effort to produce, making them a preferred choice for disseminating course materials. Despite their numerous benefits, there exists a scarcity of data-driven evidence regarding students' use of and engagement with lecture capture videos. Most existing studies rely on self-reported data, lacking comprehensive insights into students' actual video engagement. This research endeavor sought to bridge this gap by investigating university students' engagement patterns while watching lecture capture videos. To achieve this objective, we conducted an analysis of a large-scale dataset comprising over one million rows of video interaction logs. Leveraging clustering and process mining methodologies, we explored the data to reveal valuable insights into students' video engagement behaviors. Our findings indicate that in approximately 60% of students' video-watching sessions, only a small portion of the videos (an average of 7%) is watched. Our results also show that visiting the video page does not necessarily mean that the student watched it. This study may contribute to the existing literature by providing robust data-driven evidence on university students' lecture capture video engagement patterns. It is also expected to contribute methodologically to capturing, preprocessing, and analyzing students' video interactions in different contexts.

Keywords: lecture capture video, video analytics, engagement pattern, data-driven evidence, video interaction log

Introduction

The incorporation of videos in education has its roots in distance learning, where television-recorded videos were used for their unique delivery, presentation, and control features (Bates, 1988). In the last decades, in higher education, digital videos have been increasingly used in online or blended courses. If integrated properly, videos can enhance teaching and result in higher learning gains (Ahmet et al., 2018). Videos can provide a dynamic and engaging way for students to access and retain information, as they can pause and rewind videos to better understand difficult concepts. The literature provides sufficient evidence regarding the benefits of video use in higher education. For example, Carmichael et al. (2018) showed that videos can promote flexibility and independence of students as learning agents, which may increase their motivation to study and learn. Moreover, videos can increase students' satisfaction with learning environments (Choe et al., 2019; Nagy, 2018) and positively affect students' achievement (Eidenberger & Nowotny, 2022). With the global growth of online learning, videos have become even more essential in higher education to create flexible and effective learning experiences for students.

The types of educational videos may range from lecture captures to demonstrations, from animated explanations to interactive tutorials (Winslett, 2014). Although most video types require a tedious time-consuming production process, lecture videos that are unedited recordings of an instructor delivering an online or in-person lecture are exceptional. These videos are commonly called lecture captures (Owston et al., 2011), and they can be readily available to students soon after the lectures. Lecture captures can play quite an important role in reinforcing student learning after class (Giannakos et al., 2013). The prominence of lecture captures has increased significantly during the COVID-19 pandemic due to the abrupt shift to online lecturing all around the world (Pal & Patra, 2021; Tabakin et al., 2021; Wang et al., 2022). A recent study by Fina et al. (2023) also highlighted that videos in the lecture capture format are becoming a new standard in pharmacy education since the pandemic.

Although video lecture materials hold a significant place in online learning environments, the primary data source in learning analytics studies has been the log records of learning management systems. The main reason for this is that learning management systems automatically record the interaction data used in learning analytics research. However, many learning management systems only store superficial information such as whether the webpage containing the video was visited with regard to students' video interactions. In other words, they do not record data on students' interactions with the video. Meanwhile, a considerable portion of the studies examining students' video interactions are carried out within the context of massive open online courses (MOOCs; Yürüm et al., 2023). The main reason for this is that the open-source platforms used to create MOOCs (e.g., edX) automatically record video interactions. Research conducted within the MOOC context has significantly contributed to our understanding of how MOOC learners interact with videos (Kim et al., 2014) and helped identify distinct student profiles based on their video-engagement behaviors (Belarbi et al., 2019). The insights gained from previous studies have offered important implications for the design of instructional videos and the implementation of video-based learning (Guo et al., 2014).

However, findings from MOOC contexts may not apply well to the case of lecture captures especially in blended learning contexts. In MOOCs, the primary mode of instruction is through a series of short, segmented video modules (Diver & Martinez, 2015); on the other hand, lecture captures are lengthy video recordings of entire lectures and serve as a supplementary learning resource to complement the main lecturing. Therefore, the way university students interact with lecture captures is likely to differ significantly from how diverse MOOC learners interact with brief, divided videos. Nonetheless, there is scarce data-driven research on the identification of engagement with lecture captures, and still little is known about how university students benefit from them to improve their learning.

This study aimed to address the aforementioned gap through an examination of the video-watching behaviors of university students when engaging with lecture capture videos. Using techniques from cluster analysis and process mining, we examined the large dataset, containing more than one million video interactions (e.g., play, pause, seek, etc.), to uncover significant patterns in students' video engagement. This investigation enriches the current literature by providing a comprehensive, data-driven understanding of university students' engagement with lecture capture videos. Specifically, the following research questions were addressed.

1. What patterns of video engagement do students commonly exhibit while watching lecture captures?
2. What are the process models that characterize the prominent video engagement patterns exhibited by students?

The remainder of the study is structured as follows: in the second section, related literature is presented; in the third section, the method of the study is explained, followed by the results and a discussion of the main findings; and in the last section, concludes the study and provides suggestions for future research and practice.

Literature Review

Learning Strategies

Students usually demonstrate strategic behaviors while engaging with learning materials (Gasevic et al., 2017). For example, while some students might allocate more time to study in advance, others may tend to spend their time catching up (Nguyen et al., 2018). Such strategic learning behaviors are typically framed under the theories of self-regulated learning (SRL; Roll & Winne, 2015). According to SRL theories, students are active participants in their own learning process, where metacognitive strategies, such as planning, monitoring, and evaluating, play an important role (Pintrich, 2000; Zimmerman, 2000).

While previous SRL research primarily used self-report data to measure SRL behavior (Rovers et al., 2019), the emergence of the learning analytics field has popularized the use of interaction logs in identifying students' SRL-related behaviors (Wilson et al., 2021). Among others, unsupervised machine learning methods such as clustering and sequence mining have been the most widely used learning analytics approaches to detect students' engagement behaviors (Mirriahi et al., 2016; Walsh & Rísquez, 2020). While these behaviors are typically known as learning behavior or behavioral patterns (Cicchinelli et al., 2018; Kokoç et al., 2021), other researchers interpreted student behavior as a sequence of student actions forming "learning tactics" and suggested that the combination of these tactics shapes students' learning strategies (Fan et al., 2021).

Students demonstrate similar strategic behaviors to regulate their engagement with educational videos. The term *video analytics* serves as an umbrella to encompass the research studies that employ video interaction logs to identify and interpret student behavior. Video analytics aims to help educators, researchers, and instructional designers better understand and improve video-based learning and teaching (Mirriahi & Vigentini, 2017). The following section presents a synthesis of video analytics studies.

Video Analytics

Researchers have used students' video interaction logs to explore answers to different research questions. For example, Merkt et al. (2022) analyzed students' pausing behavior in educational videos. They observed instances where students faced difficulties or identified meaningful structural breakpoints in the video content. The findings revealed that students' pausing behavior was significantly influenced by their perception of difficulty and meaningful breakpoints in the video. In another study, Zhang et al. (2022) analyzed video lecture engagement patterns for evidence that learners exhibit a selective and purpose-driven approach. Indeed, the learners preferred content aligned closely with their learning objectives, often skipping introductory or less relevant material. This trend was particularly noticeable in videos covering advanced concepts, which captured significant attention and engagement. Conversely, introductory videos, typically covering course overviews and methodologies, were less frequently watched, suggesting that learners either had pre-existing familiarity with the course structure or preferred to engage directly with more substantive content. Re-watching behavior indicated that learners revisited specific sections or concepts instead of re-engaging with entire videos. Videos that were re-watched more frequently tended to have higher technical content or unique instructional methods, suggesting that content complexity and engaging delivery styles were factors prompting repeat viewings.

Guo et al. (2014) showed that while learners watch lecture videos more linearly, they demonstrate seeking or searching behavior more frequently in tutorial videos. They also found that students show a high number of re-watch behaviors in non-visual explanations or in sections where an important theory or topic is explained. It means that the parts of the video that are hard to understand or that are perceived to be important are often watched. While some students skip the initial parts of the video material, others visit the missed content. Akçapınar and Bayazıt (2018) compared deep and surface learners' video-watching behaviors in terms of interactions such as play, pause, seek forward, and seek backward. They found that surface learners made more seeks forward than deep learners who watched videos with more seeks backward.

Methodology

Research Context

The context of this study was five courses conducted remotely by the same instructor using the Moodle learning management system (LMS) during the COVID-19 pandemic. These courses consisted of compulsory and elective courses for undergraduate students of the Educational Technology Department at Hacettepe University, Türkiye. While the total number of students enrolled in the courses was 451, the number of students who had at least one video-watching session was 381. Excluding students enrolled in more than one course, the total number of unique students was 181. The video type used in all courses was the same, and they were lecture captures. These videos were Zoom recordings of live lecture sessions with students present. Video lengths ranged from 13 minutes to 100 minutes, with an average video length of 64 minutes. Video contents were in the form of presentation and screen sharing. A similar learning design was used in all courses. Course activities such as assignments, quizzes, discussion forums, Sharable Content Objects (SCOs), and live lecture video recordings (lecture captures) were used in the lessons.

Data Collection Tool

The data were collected with a video player developed by the authors, which is integrated into the Moodle LMS. Through this JavaScript-based video player, students' video interactions (play, pause, seek, etc.) were recorded in the database as time-stamped events. The events recorded by the video player and their descriptions are presented in Table 1. Using this video player, more than one million rows of click-stream data were obtained from 4,402 unique video-watching sessions pertaining to 74 videos.

Table 1

Types of Events Logged by the Video Player

Event	Description
Load	Video loaded
Play	Play button pressed
Pause	Video paused
Seek	Jumped forward or backward in the video
Time Update	Video playing (automatically generated every 5 seconds)
End	Video finished

Data Analysis Techniques

Cluster and process mining analysis were used to understand students' video engagements. Cluster analysis is a technique for grouping entities based on their common characteristics (Ungar & Foster, 1998). Based on the attributes of the entities, the algorithm divides the similarities among the individuals in the data set into a small number of sub-groups. In most cases, after the application of clustering analysis, the characteristics of the groups formed are discovered, similarities of the individuals or objects in the groups are revealed, and these groups are named with cluster labels (Yoon et al., 2021). On the other hand, process mining focuses on extracting process-related knowledge from event logs and other data sources. Process mining uses information systems' event logs to uncover, monitor, and enhance processes in different areas (Cairns et al., 2015). An event log may be thought of as a collection of traces. In terms of the actions performed, each trace reflects the life cycle of a process instance. Additional information about events, the resource executing or starting the action, the timing of the event, and data items associated with the event are frequently stored in event logs (van der Aalst, 2019).

Data Analysis

Before the analysis, the raw interaction data were preprocessed which first involved extracting the video-watching sessions. In this paper, a session is considered a time frame of interactions with a specific video after the video is loaded. A video-watching session starts with the Load event, which indicates that the page with video content is loaded in the Moodle environment. In other words, each Load event is considered the start of a new video-watching session. All video interaction events until the same or a different video is loaded (e.g., until a new Load event comes) are considered to be within the same session.

Since the number of activities that students perform in each video-watching session is variable, clustering them as they are will not fully answer our research questions. Therefore, in this study, we followed a novel approach in which students' interactions were transformed into standard sequences over the video timeline. In this way, it was also possible to align the sessions. The steps for this transformation process were as follows: First, video lengths were standardized between 0 and 100, as the videos were of varying lengths. In other words, the videos were analyzed by dividing them into 100 equal units. The student's engagement in each unit was labeled as unseen, active, or passive. Unseen indicated no interaction at a specific unit, suggesting that the student did not watch that part of the video (skipped it or never saw it). If the student had an interaction log on that unit, such as pausing, playing, or seeking, this situation was labeled as active (i.e., active engagement). This label indicated that the student was actively engaged with the video at that specific unit. Finally, if student interaction at a specific unit was in the form of a Time Update (automatic progress event—see Table 1), then the passive label was used (i.e., passive engagement). This label represented the situations where students watched the relevant section without any interaction. Thanks to this labeling, it was possible to identify the moments of videos that students watched or not as well as their engagement (i.e., active or passive) regardless of video length.

In order to extract different video-watching patterns, the video-watching sessions of the students were grouped using sequence clustering analysis. The preprocessing steps carried out resulted in the representation of video sessions as sequences of video interaction events in a timeline divided by 1% segments in each lecture capture video. This representation was used to perform a clustering analysis based on the sequences of interaction events and identify distinct video-watching behaviors where the interactions unfold in varying orders and times. Data preprocessing was done automatically with the help of a tool developed by the authors. Clustering analysis was performed with the TraMineR (Gabadinho et al., 2011) package in the R software (Version 4.3.1). In order to describe the characteristics of the sessions in the clusters, descriptive statistics (e.g., mean, standard deviation, percentiles) were used. The metrics used to characterize sessions in each cluster and their descriptions are presented in Table 2.

Table 2

Description of Video Interaction Metrics

Metric	Description
session_duration	Duration of a session in terms of minutes
total_action	Total number of actions in a session
play	Number of times a play button was pressed in a session
pause	Number of times a pause button was pressed in a session
backward	Number of times a video was backwarded in a session
forward	Number of times a video was forwarded in a session
time_update	Number of times time update event was recorded while watching a video
max_percent	The maximum point reached in the timeline of the video in terms of percentage
total_percent	Total percentage of video portion watched

Finally, the process mining analysis was performed using the Disco process mining software (Version 3.6.7) to reveal the interaction patterns of students in the video-watching sessions in different clusters. In this way, we aimed to reveal the interaction sequences of students in the video-watching sessions. For process mining analysis, the video-watching sessions in each cluster were organized as timed event logs.

Results

We present our results under two subheadings that refer to our research questions; the first concerns engagement patterns, while the second deals with process models that characterize these engagement patterns.

Research Question 1: What patterns of video engagement do students commonly exhibit while watching lecture captures?

The cluster analysis yielded four groups of sessions with distinct video engagement behavior, as shown in Figure 1. For each subplot in this figure, the x-axis represents the video timeline divided into 1% segments, while the y-axis represents individual video-watching sessions. Within the subplots, video segments skipped are indicated in white, segments passively watched are blue, and segments where students interacted with the video (e.g., pausing or skipping) are red.

In the first group, shown in Figure 1A (n = 2,565, 58% of all sessions), students barely watched the videos. This is represented by the large white area. In 50% of these sessions, students spent less than 1.8 minutes and watched only 6% (or less) of the videos.

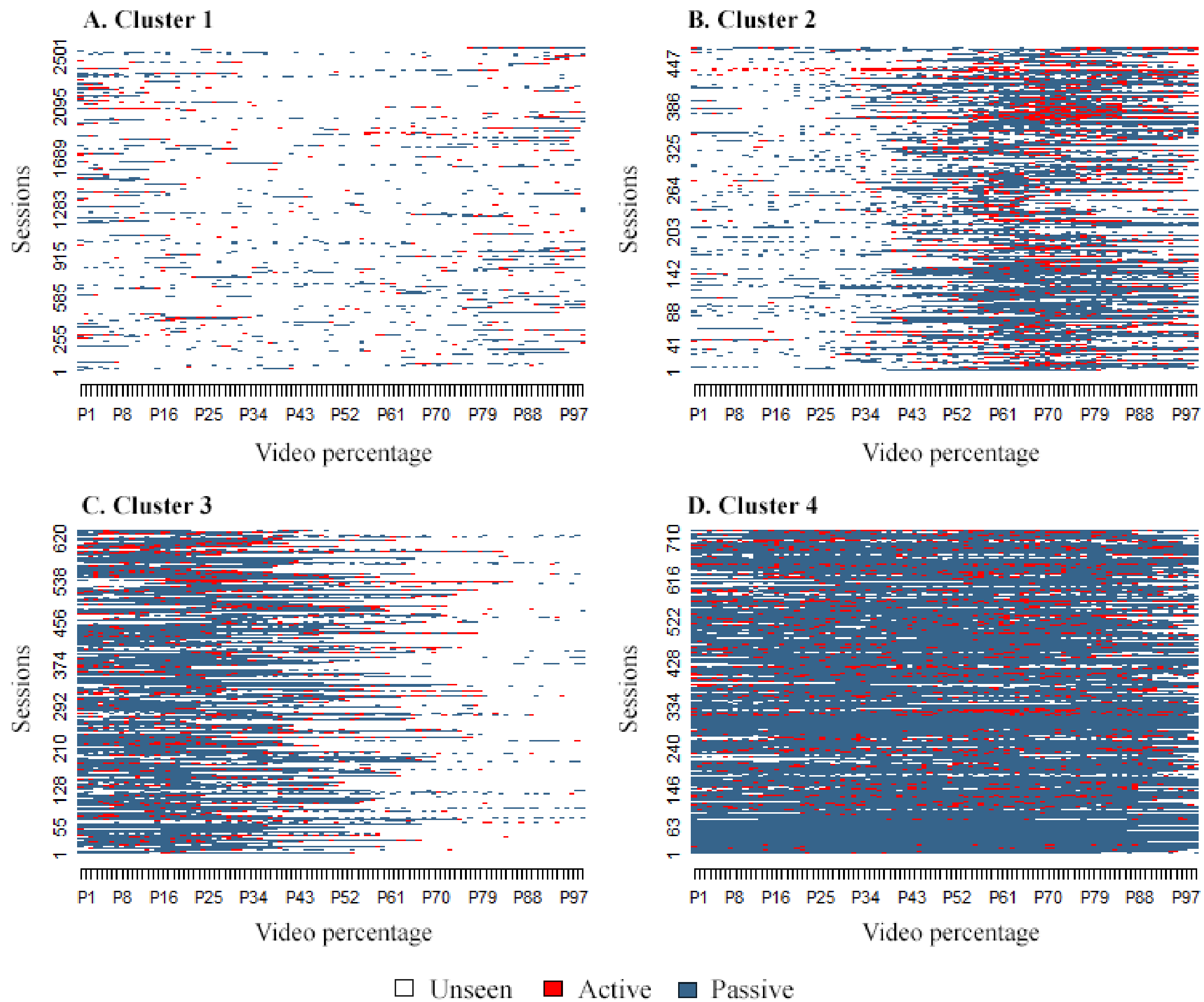
In the second group, shown in Figure 1B (n = 472, 38% of all sessions), students engaged mostly with the second half of the videos and discarded the first half. This is represented by extensive white on the left side of the panel, whereas on the right, blue and red are the dominant colors. In 50% of the sessions in this group, students stayed on the videos 29.45 minutes at maximum, and they watched 38% (or less) of the videos.

Moreover, Figure 1C, which represents 17% of the sessions (n = 637), demonstrates a different student behavior that involves engagement with the first part of the videos, opposite to what is seen in Figure 1B. In these sessions, students watched and/or interacted with videos mostly until around the midpoint of the timeline, but they began to disengage thereafter. In 50% of the sessions represented in this cluster, students stayed with the video for 32.5 minutes at maximum, while they watched 39% (or less) of the total videos.

Last, Figure 1D represents 14% of the sessions (n = 728). These sessions differed from the others in terms of the strength and consistency of the engagement. In 50%, students spent up to 62.8 minutes and watched 96% or less of the videos.

Figure 1

Distinct Groups of Engagement Behavior Produced in the Cluster Analysis



Note. n Cluster 1 sessions = 2,565; n Cluster 2 sessions = 472; n Cluster 3 sessions = 637; n Cluster 4 sessions = 728

Research Question 2: What are the process models that characterize the prominent video engagement patterns exhibited by students?

Process mining analysis was used to mine the video interaction patterns in each cluster. The most prevalent behaviors found in these patterns, along with their descriptions, are presented in Table 3. These sequences reflect a significant part of the behaviors exhibited by students during the video-watching sessions.

Table 3

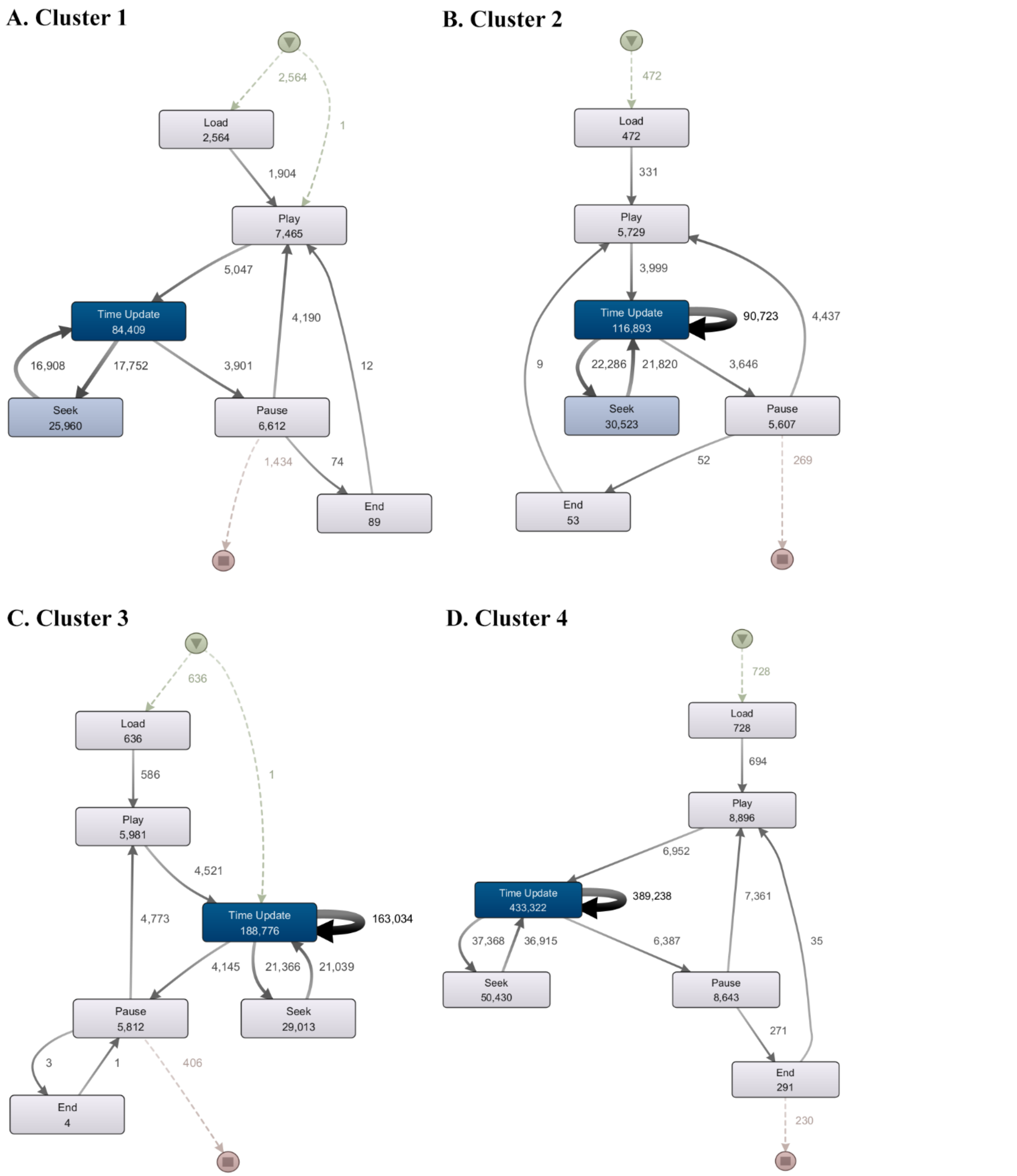
Students' Video Interaction Sequences and Descriptions

Sequence	Description
Load → Play	After the video is loaded, the student plays it from the beginning.
Load → Seek	As soon as the video is loaded, the student moves to a later section.
Time Update → Time Update	The student continues to watch the video without any interaction.
Time Update → Pause	The student pauses the video.
Pause → Play	The student plays the paused video.
Play → Time Update	The student plays the video and continues to watch it.
Time Update → Seek	While watching it, the student jumps forward or backward in the video.
Seek → Time Update	After jumping forward or backward, the student continues to watch the video.
Seek → Seek	The student continuously jumps forward or backward in the video.
Seek → Pause	After jumping forward or backward, the student pauses the video.
Seek → Play	After jumping forward or backward, the student plays the video.

The most frequently encountered patterns in the sessions in each cluster are visually presented as process maps in Figure 2. In the process models, only the prominent paths are included to make the graphics look plain, but all paths were considered when explaining the process models.

Figure 2

Process Models of Student Interactions in Each Cluster



Note. In the process model, the triangle symbol represents the start of the process, while the endpoint is indicated by the stop symbol. Activities are depicted as boxes and the process flow between activities is illustrated by an arrow.

Dashed arrows indicate activities at the beginning and end of the process. The numbers inside the boxes and next to the arrows signify the absolute frequencies. The thickness of the arrows and the coloring of the boxes reflects these numerical values (Fluxicon, 2024).

Figure 2A shows that the videos were loaded 2,564 times in total during the sessions in Cluster 1. The Load event is followed by the Play event by 74% (Load → Play) and by the Seek event by 25% (Load → Seek). The Play event is followed by the Time Update event at a rate of 68% (Play → Time Update) and a Pause event by 20% (Play → Pause). In 10%, the Seek event follows (Play → Seek). The Time Update event, which indicates that the video was being viewed, is followed by the Time Update event at 74%, while the Seek event is followed by 21%. The Seek event is followed by the Time Update event in 68%, while the Seek event is followed by another Seek event in 24%.

Figure 2B shows that the videos were loaded 472 times in the sessions in Cluster 2. The Load event is followed by the Play event at 70% (Load → Play) and the Seek event at 30% (Load → Seek). After the Play event, 70% were a Time Update event (Play → Time Update) and 20% a Pause event (Play → Pause). In 10%, the Seek event follows (Play → Seek). The Time Update event, which indicates that the video is being watched, is followed by the Time Update event at 78% and the Seek event at 19%. The Seek event is followed by Time Update at 71%, while the Seek event is followed by another Seek event at 23%.

Figure 2C shows that the videos were loaded 636 times in the sessions in Cluster 3. The Load event is followed by the Play event at 92% (Load → Play), while the Seek event represents only 0.04% (Load → Seek). After the Play event, the Time Update event comes at a rate of 75% (Play → Time Update) and the Pause event at a rate of 22% (Play → Pause). Only 1% follow the Seek event (Play → Seek). The Time Update event, which indicates that the video is being watched, is followed by another Time Update event at 86% and the Seek event at 11%. While the Seek event is followed by Time Update at 72%, it is followed by the Seek event again at 23%.

Finally, Figure 2D shows that the videos were loaded 728 times in the sessions in Cluster 4. The Load event is followed by the Play event at 95% (Load → Play) while the Seek event represents only 0.04% (Load → Seek). After the Play event, the Time Update event comes at a rate of 78% (Play → Time Update) and the Pause event at a rate of 16% (Play → Pause). Only 1% follow the Seek event (Play → Seek). The Time Update event, which indicates that the video is being watched, is followed by another Time Update event at 90% and the Seek event at 9%. The Seek event is followed by Time Update in 73%, while the Seek event is followed again in 24%.

When each cluster was evaluated in terms of prominent patterns, a few noteworthy points emerged. Although 58% of the analyzed video sessions are in Cluster 1, when the interactions in the sessions are examined, it is seen that the least number of interactions occurred here. On the other hand, it is seen that the sessions with the highest value in terms of interaction took place in Cluster 4, which includes just 14% of all sessions. Since the event named Time Update is created automatically at 5-second intervals, it is an expected result that there would be the largest number of such events in all models.

Discussion

In this study, the video-watching behaviors of university students were analyzed, focusing on their interaction with lecture capture videos. For this purpose, a total of 4,402 video-watching sessions were identified and processed to label video segments that students watched, actively or passively engaged with, or did not watch. Subsequently, the video-watching sessions were clustered to identify prominent viewing behaviors, and process models were examined for each cluster.

The cluster analysis yielded four groups of behavioral patterns. Although the sessions in Cluster 1 were abundant, students engaged in rather superficial activities during these sessions. The low duration of video viewing, low number of activities, predominance of unwatched sections in the video, and distribution of activities across different regions of the video timeline may indicate that students were browsing for information in these sessions. The process model associated with Cluster 1 also suggests a non-linear, skipping-based viewing pattern, implying that these sessions may be more related to skimming rather than learning. Alternatively, students may have exhibited this behavior to locate specific topics covered in videos. This behavior may also be related to students' approaches to learning. For instance, a study conducted by Akçapınar and Bayazıt (2018) revealed that students with a surface learning approach tended to skip forward more while watching videos. Yoon et al. (2021) referred to the behavioral pattern of superficial interaction with the video player as "browsing." They also found that students who exhibited only this behavior pattern had lower learning achievement. Considering that the content was derived from lecture captures, an alternative interpretation of these findings could be that students were promptly revisiting the videos to reinforce and deepen their conceptual understanding after participating in the live lecture sessions. This behavior may suggest a proactive approach to learning, using the recorded lectures as a tool for revision and comprehension enhancement.

In the video viewing sessions within Cluster 2, it is observed that students tended to skip the initial part of the videos but actively engaged with a specific section. This viewing behavior could be related to video design or course design. In the analyzed courses, students were given an assignment at the end of the lesson, and the details of this assignment were explained during the lesson. Therefore, some students might have re-watched the relevant section of the lesson while working on the assignment. Yoon et al. (2021) referred to similar behavior as "information seeking" which involves cognitive efforts to retrieve and organize information. Seo et al. (2021) considered these behaviors as "search," based on students' self-reported intentions.

In the video-watching sessions within Cluster 3, it is observed that students watched the initial part of the videos but ended the session without watching the final part. While some of these sessions may indicate passive engagement, in others, students actively engaged with the initial part of the video. This may be due to the longer duration of the videos, particularly in lecture captures that cover the entire lesson. These videos may contain irrelevant information, such as dialogues happening during the lecture, which can also affect the flow of the lesson. Consequently, the lesson may not go as planned, creating uncertainty for students and leading them to leave the video without watching it entirely. Students may get bored, disoriented, or feel lost due to the lack of guiding information within the videos. Kim et al. (2014) analyzed user interactions in 862 videos from four different MOOCs on the edX platform and found that video length and video type were significant variables in predicting students' video dropout. They also found that the dropout rate increased with video length. Another study conducted by Guo et al. (2014) examined approximately seven million video sessions on the edX platform and investigated the relationship between video design and student engagement. The research findings indicated that shorter videos were more engaging, while pre-recorded classroom lectures, even when presented in smaller chunks, were less engaging compared to other video types.

In the video-watching sessions within Cluster 4, it is observed that students mostly watched the videos from start to finish. However, upon visual analysis, it is noticed that in some of these sessions, students passively watched the videos without engaging in any activity. Students may exhibit this behavior believing that their video-watching will impact their final scores. This behavior could be related to gaming (Baker et al., 2008) or off-task behavior. In the other part of these sessions, more active engagement is observed with activities such as pausing, playing, and skipping. Seo et al. (2021) explored how students' video-watching activities map to different engagement goals and intents. Some of the mappings found between active video engagement and video activities are as follows: Students reported that they often pause to summarize in their notebooks. They often rewound when they wanted to make sure they did not miss anything or when they did not get the explanation the first time.

Conclusion

Although lecture capture videos may not be considered best practice from the perspective of multimedia learning theory (Clark & Mayer, 2016), they are often preferred by teachers due to their ease of preparation. Studies based on self-report data also indicate that students have positive perceptions of lecture captures (Dommett et al., 2020). However, the widespread use of lecture capture or positive student perceptions does not provide evidence of their actual usage. Therefore, this study has focused on actual usage data to provide evidence-based insights into students' engagement with the lecture capture videos. Our results showed that most of the video-watching sessions examined (58%) consisted of superficial interactions. Moreover, in only a small number of sessions, students actively watched the video from start to finish. In other sessions, they actively watched only a part of the video.

Limitations

The scope of this research study is limited to the use of click-stream data to identify common behavioral patterns; however, it doesn't delve into the underlying motivations behind students' specific engagement with the videos. Aspects such as the level of attentiveness of students during video viewing and its correlation with the nature of the video content were not investigated in this study. This leaves room for further exploration.

Implications

The findings of this research offer important implications for designing more effective video-based learning environments. Within large lecture capture videos, instructors can mark the time points where specific topics are taught or discussed during the lectures to help students browse through videos more effectively. For example, the instructor can mark the moment when the assignment is discussed, which would allow students to easily refer back to the instructions when working on the assignment. Moreover, although lecture captures have the advantage of being quickly available to students, their segmentation into smaller, manageable portions might be more desirable for several reasons. These segments can focus on specific topics, which may allow students to easily locate and revisit specific sections for reinforcement of concepts.

In the field of learning analytics, sequence analyses are applied to click-stream data to identify similar sequences of student or learning sessions. The commonly used approach for this purpose is clustering the clickstreams of students' learning sessions as they are. However, clustering similar sessions becomes challenging due to the varying number of interactions in these sessions. In this study, students' video-watching sessions were processed using a custom script developed by the researchers and transformed into standard sequences before applying the clustering process. This also allowed for the alignment of sessions in a similar manner, despite differences in video lengths and activity counts in the sessions.

Future Directions

This study presents a novel approach to the analysis of video-watching sessions. By using this approach, answers to different research questions can be sought in future studies. For instance, future research can analyze how students' video-watching behaviors vary over time and across tasks. Similarly, it can be determined whether these watching behaviors are individual characteristics of students or if they are employed as a temporal strategy. The process mining analysis used in this study has shown that three different watching behaviors are commonly used: linear, pausing and replaying, and skipping. It is important to analyze in future studies when students exhibit these behaviors and which watching behaviors are more related to learning outcomes. Moreover, employing a similar approach, the impact of modifications in video design (such as dividing videos into smaller segments based on topics or incorporating markers on the video timeline indicating different topics) on students' video-watching behaviors can be investigated. This would enable the acquisition of data-driven evidence to maximize the benefits derived from commonly used and highly preferred video materials in educational environments. Also, the frequency of students' video visits and the time delay between them could provide additional insights into students' video engagement. Future research can explore these aspects to identify other student behaviors, such as the tendency of specific student groups to rewatch videos, and the videos that were more frequently visited by students.

References

Ahmet, A., Gamze, K., Rustem, M., & Sezen, K. A. (2018). Is video-based education an effective method in surgical education? A systematic review. *Journal of Surgical Education*, *75*(5), 1150–1158. https://doi.org/10.1016/j.jsurg.2018.01.014

Akçapınar, G., & Bayazıt, A. (2018). Investigating video viewing behaviors of students with different learning approaches using video analytics. *The Turkish Online Journal of Distance Education*, *19*(4), 116–125. https://doi.org/10.17718/tojde.471907

Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., & Koedinger, K. (2008). Why students engage in “gaming the system” behavior in interactive learning environments. *Journal of Interactive Learning Research*, *19*(2), 185–224. https://www.learntechlib.org/p/24328/

Bates, A. W. (1988). Television, learning and distance education. *Journal of Educational Television*, *14*(3), 213–225. https://doi.org/10.1080/0260741880140305

Belarbi, N., Chafiq, N., Talbi, M., Namir, A., & Benlahmar, E. (2019). User profiling in a SPOC: A method based on user video clickstream analysis. *International Journal of Emerging Technologies in Learning (iJET)*, *14*(01), 110–124. https://doi.org/10.3991/ijet.v14i01.9091

Cairns, A. H., Gueni, B., Fhima, M., Cairns, A., David, S., Khelifa, N., & Dautier, P. (2015). Process mining in the education domain. *International Journal on Advances in Intelligent Systems*, *8*, 219–232.

Carmichael, M., Reid, A., & Karpicke, J. D. (2018). *Assessing the impact of educational video on student engagement, critical thinking and learning*. Sage Publishing. https://us.sagepub.com/sites/default/files/hevideolearning.pdf

Choe, R. C., Scuric, Z., Eshkol, E., Cruser, S., Arndt, A., Cox, R., Toma, S. P., Shapiro, C., Levis-Fitzgerald, M., Barnes, G., & Crosbie, R. H. (2019). Student satisfaction and learning outcomes in asynchronous online lecture Videos. *CBE—Life Sciences Education*, *18*(4), Article 55. https://doi.org/10.1187/cbe.18-08-0171

Cicchinelli, A., Veas, E., Pardo, A., Pammer-Schindler, V., Fessl, A., Barreiros, C., & Lindstädt, S. (2018). Finding traces of self-regulated learning in activity streams. In A. Pardo, K. Bartimote-Aufflick, & G. Lynch (Chairs), *LAK ’18: Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 191–200). Association for Computing Machinery. https://doi.org/10.1145/3170358.3170381

Clark, R. C., & Mayer, R. E. (2016). *E-learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning*. John Wiley & Sons. https://doi.org/10.1002/9781119239086

Diver, P., & Martinez, I. (2015). MOOCs as a massive research laboratory: Opportunities and challenges. *Distance Education*, *36*(1), 5–25. https://doi.org/10.1080/01587919.2015.1019968

Dommett, E. J., Gardner, B., & van Tilburg, W. (2020). Staff and students perception of lecture capture. *The Internet and Higher Education*, *46*, Article 100732. https://doi.org/10.1016/j.iheduc.2020.100732

Eidenberger, M., & Nowotny, S. (2022). Video-based learning compared to face-to-face learning in psychomotor skills physiotherapy education. Creative Education, 13(1), 149–166. https://doi.org/10.4236/ce.2022.131011

Fan, Y., Matcha, W., Uzir, N. A., Wang, Q., & Gašević, D. (2021). Learning analytics to reveal links between learning design and self-regulated learning. *International Journal of Artificial Intelligence in Education*, *31*(4), 980–1021. https://doi.org/10.1007/s40593-021-00249-z

Fina, P., Petrova, T., & Hughes, J. (2023). Lecture capture is the new standard of practice in pharmacy education. *American Journal of Pharmaceutical Education*, *87*(2), Article ajpe8997. https://doi.org/10.5688/ajpe8997

Fluxicon. (2024, February 08). Process Mining in Practice. https://fluxicon.com/book/read/mapview/Gabadinho, A., Ritschard, G., Müller, N. S., & Studer, M. (2011). Analyzing and visualizing state sequences in R with TraMineR. *Journal of Statistical Software*, *40*(4), 1–37. https://doi.org/10.18637/jss.v040.i04

Gasevic, D., Jovanovic, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: Links with self-reported measures and academic performance. *Journal of Learning Analytics*, *4*(2), 113–128. https://doi.org/10.18608/jla.2017.42.10

Giannakos, M. N., Chorianopoulos, K., Ronchetti, M., Szegedi, P., & Teasley, S. D. (2013). Analytics on video-based learning. In D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *LAK '13: Third Conference on Learning Analytics and Knowledge, Leuven, Belgium, April 8–13, 2013* (pp. 283–284). Association for Computing Machinery. https://doi.org/10.1145/2460296.2460358

Guo, P. J., Kim, J., & Rubin, R. (2014). How video production affects student engagement: An empirical study of MOOC videos. In M. Sahami (Chair), *L@S 2014: First (2014) ACM Conference on Learning @ Scale, Atlanta, Georgia, USA, March 4–5, 2014* (pp. 41–50). Association for Computing Machinery. https://doi.org/10.1145/2556325.2566239

Kim, J., Guo, P. J., Seaton, D. T., Mitros, P., Gajos, K. Z., & Miller, R. C. (2014). Understanding in-video dropouts and interaction peaks in online lecture videos. In M. Sahami (Chair), *L@S 2014: First (2014) ACM Conference on Learning @ Scale, Atlanta, Georgia, USA, March 4–5, 2014* (pp. 31–40). Association for Computing Machinery. https://doi.org/10.1145/2556325.2566237

Kokoç, M., Akçapınar, G., & Hasnine, M. N. (2021). Unfolding students' online assignment submission behavioral patterns using temporal learning analytics. *Educational Technology & Society*, *24*(1), 223–235. https://www.jstor.org/stable/26977869

Merkt, M., Hoppe, A., Bruns, G., Ewerth, R., & Huff, M. (2022). Pushing the button: Why do learners pause online videos? *Computers & Education*, *176*, Article 104355. https://doi.org/10.1016/j.compedu.2021.104355

Mirriahi, N., Liaqat, D., Dawson, S., & Gašević, D. (2016). Uncovering student learning profiles with a video annotation tool: Reflective learning with and without instructional norms. *Educational Technology Research and Development*, *64*(6), 1083–1106. https://doi.org/10.1007/s11423-016-9449-2

Mirriahi, N., & Vigentini, L. (2017). Analytics of learner video use. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), Handbook of learning analytics (1st ed., pp. 251–267). The Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17.022

Nagy, J. T. (2018). Evaluation of online video usage and learning satisfaction: An extension of the technology acceptance model. *The International Review of Research in Open and Distributed Learning*, *19*(1). https://doi.org/10.19173/irrodl.v19i1.2886

Nguyen, Q., Huptych, M., & Rienties, B. (2018). Using temporal analytics to detect inconsistencies between learning design and students' behaviours. *Journal of Learning Analytics*, *5*(3), 120–135. https://doi.org/10.18608/jla.2018.53.8

Owston, R., Lupshenyuk, D., & Wideman, H. (2011). Lecture capture in large undergraduate classes: Student perceptions and academic performance. *The Internet and Higher Education*, *14*(4), 262–268. https://doi.org/10.1016/j.iheduc.2011.05.006

Pal, D., & Patra, S. (2021). University students' perception of video-based learning in times of COVID-19: A TAM/TTF perspective. *International Journal of Human–Computer Interaction*, *37*(10), 903–921. https://doi.org/10.1080/10447318.2020.1848164

Pintrich, P. R. (2000). Chapter 14 - The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, *2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2

Rovers, S. F. E., Clarebout, G., Savelberg, H. H. C. M., de Bruin, A. B. H., & van Merriënboer, J. J. G. (2019). Granularity matters: Comparing different ways of measuring self-regulated learning. *Metacognition and Learning*, *14*(1), 1–19. https://doi.org/10.1007/s11409-019-09188-6

Seo, K., Dodson, S., Harandi, N. M., Roberson, N., Fels, S., & Roll, I. (2021). Active learning with online video: The impact of learning context on engagement. *Computers & Education*, *165*, Article 104132. https://doi.org/10.1016/j.compedu.2021.104132

Tabakin, A. L., Patel, H. V., & Singer, E. A. (2021). Lessons learned from the COVID-19 pandemic: A call for a national video-based curriculum for urology residents. *Journal of Surgical Education*, *78*(1), 324–326. https://doi.org/10.1016/j.jsurg.2020.07.013

Ungar, L. H., & Foster, D. P. (1998). Clustering methods for collaborative filtering. In *Proceedings of the AAAI Conference on Artificial Intelligence, 15*. Association for the Advancement of Artificial Intelligence (AAAI). https://api.semanticscholar.org/CorpusID:6565845

van der Aalst, W. M. P. (2019). Object-centric process mining: Dealing with divergence and convergence in event data. In P. Ölveczky & G. Salaün (Eds.), *Software Engineering and Formal Methods. SEFM 2019. Lecture Notes in Computer Science, Vol. 11724*. Springer. https://doi.org/10.1007/978-3-030-30446-1_1

Walsh, J. N., & Rísquez, A. (2020). Using cluster analysis to explore the engagement with a flipped classroom of native and non-native English-speaking management students. *The International Journal of Management Education*, *18*(2), Article 100381. https://doi.org/10.1016/j.ijme.2020.100381

Wang, X., Liu, T., Wang, J., & Tian, J. (2022). Understanding learner continuance intention: A comparison of live video learning, pre-recorded video learning and hybrid video learning in COVID-19 pandemic. *International Journal of Human–Computer Interaction*, *38*(3), 263–281. https://doi.org/10.1080/10447318.2021.1938389

Wilson, D., Wright, J., & Summers, L. (2021). Mapping patterns of student engagement using cluster analysis. *Journal for STEM Education Research*, *4*(2), 217–239. https://doi.org/10.1007/s41979-021-00049-z

Winslett, G. (2014). What counts as educational video?: Working toward best practice alignment between video production approaches and outcomes. *Australasian Journal of Educational Technology*, *30*(5). https://doi.org/10.14742/ajet.458

Yoon, M., Lee, J., & Jo, I.-H. (2021). Video learning analytics: Investigating behavioral patterns and learner clusters in video-based online learning. *The Internet and Higher Education*, *50*, Article 100806. https://doi.org/10.1016/j.iheduc.2021.100806

Yürüm, O. R., Taşkaya-Temizel, T., & Yıldırım, S. (2023). Predictive video analytics in online courses: A systematic literature review. *Technology, Knowledge and Learning*, *2023*. https://doi.org/10.1007/s10758-023-09697-z

Zhang, J., Huang, Y., & Gao, M. (2022). Video features, engagement, and patterns of collective attention allocation. *Journal of Learning Analytics*, *9*(1), 32–52. https://doi.org/10.18608/jla.2022.7421

Zimmerman, B. J. (2000). Chapter 2—Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7