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Exploring the Use of Video Analytics to Support Adaptive Learning and Student Engagement in Thailand

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Abstract: This paper presents a video-based learning system enhanced with learning analytics to monitor and analyze Thai learner behavior during video consumption. The system logs detailed interactions, including pausing, skipping, and rewinding, along with their timestamps. These interactions are quantified by frequency and duration to derive meaningful behavioral insights. An adaptive mechanism is integrated to provide personalized prompts, encouraging students to seek instructor feedback or alternative learning strategies when rapid progression through content is detected. Experimental results reveal distinct behavioral patterns of Thai students including linear viewers, pausers, skippers, rewinders, and neutral viewers. From the results, we found that 34, 24, 19, 13, and 10 percentage of participants are linear viewers, pausers, skippers, rewinders, and neutral viewers, respectively. Among these, rewinders achieved the highest average post-test score of 4.38, underscoring the benefit of content review. Frequent pausers also performed well, suggesting that reflective engagement enhances understanding. In contrast, students who skipped over half the video content scored the lowest, with an average of 1.91. These findings highlight the potential of learning analytics to support adaptive and effective video-based education for Thai students.

Keywords: Video-based Learning, Video Analytics, Learning Behavior, Adaptive Learning

1. Introduction

In the digital age, educational technology has transformed how students engage with learning content, and among these innovations, video-based learning has become a particularly effective method. Video-based learning combines visual and auditory elements, which help students better understand and retain complex concepts compared to traditional methods. Research indicates that multimedia presentations, which integrate narration and visuals, significantly enhance students' ability to grasp and remember content (Kay et al., 2022). Unlike traditional classroom instruction, video-based learning offers the flexibility for students to learn at their own pace, pausing, rewinding, or reviewing material as needed. This ability to control the learning process is particularly beneficial for students who may need additional time to grasp concepts or those who learn better through repetition. The option to pause and rewind allows learners to revisit difficult sections, ensuring they do not miss critical information and reinforcing understanding. Additionally, students can go over content multiple times to reinforce their knowledge, which is particularly helpful for complex subjects. This flexibility empowers learners to personalize their study experience and encourages active, self-directed learning, leading to improved outcomes (Mayer, 2009). Studies have shown that self-paced learning environments, such as video-based learning, lead to greater retention and mastery of content, especially for subjects that require deeper conceptual understanding (Brusilovsky & Millán, 2007).

One major challenge in modern education is implementing personalized learning, which tailors teaching methods, content, and pace to each student's unique needs. Although personalized learning has the potential to improve student engagement and performance, it is difficult to apply in large or traditional classrooms due to constraints like limited time, the lack of real-time data on student progress, and teachers' heavy workloads (Pane et al., 2017). Video analytics, however, offers a promising solution to these challenges by providing educators with actionable insights into how students interact with learning content. Unlike traditional methods, video analytics tracks students' engagement with video-based learning materials in real time, capturing data on viewing patterns, attention levels, and areas where students struggle. This data enables teachers to identify individual learning needs more quickly and accurately, allowing them to tailor instruction or intervene when necessary (Arroyo et al., 2014). By combining video-based learning with analytics tools, educators can create more personalized learning experiences, giving students the flexibility to learn at their own pace while also receiving targeted feedback based on their behavior (Jovanović et al., 2017). In the context of Thailand, where disparities in digital literacy and access to resources remain significant challenges, integrating video analytics can help bridge the gap by providing teachers with valuable data to improve student outcomes , even in resource-constrained environments (Aroonsrimarakot et al., 2023) (Suwanwimolkul & Singhalertchai, 2021).

This paper presents a study on how video analytic tools can enhance adaptive learning for Thai students by supporting more personalized and data-informed instruction. It focuses on the design and initial implementation of a video analytics system intended to capture learner behavior during video-based activities and offer insights that align with students' needs. As this approach is still new in the Thai educational context, the study emphasizes designing the system to fit existing teaching practices and technological conditions. Through a comparative experiment involving students who engage with standard video content and those using an analytics-enhanced video platform, the research investigates how such tools might influence student engagement and inform instructional adjustments. Expected outcomes include increased engagement among students using the enhanced platform and the identification of behavioral patterns that can support the development of more adaptive learning strategies.

2. Literature Reviews

In recent years, the demand for more flexible, engaging, and personalized learning experiences has driven the integration of technology into educational environments. Among the growing innovations, two interrelated developments have gained particular attention: the rise of video-based learning and the evolution of adaptive learning systems powered by multimedia and learning analytics. These approaches not only offer scalable solutions for improving student engagement but also hold the potential to address the challenges of personalized instruction in diverse educational settings such as Thailand. In this secton, we explore the existing research on (1) video-based learning and the application of learning analytics to monitor and improve student engagement, and (2) adaptive learning systems that utilize multimedia to tailor educational content to individual learners' needs. Together, these strands of research provide the foundation for investigating how video analytics can be leveraged to support adaptive learning in practice.

2.1 Video-Based Learning and Learning Analytics

Video-based learning has gained widespread popularity in educational settings due to its flexibility and accessibility. It offers students the opportunity to learn at their own pace and revisit content as needed. Several studies have highlighted the positive impact of video-based learning, especially when paired with interactive elements and effective instructional design.

Guo, Kim, and Rubin (2014) examine the relationship between video production quality and student engagement in Massive Open Online Courses (MOOCs). They find that production quality, such as clear audio, well-paced content, and engaging visuals, significantly increases student retention and engagement. The study underscores the potential of highquality instructional videos in enhancing student engagement. In addition, Kay, Leung, and Tang (2022) provide a comprehensive systematic review of the effectiveness of instructional videos in higher education. The authors summarize the benefits of video-based learning, including the ability to cater to diverse learning styles and allow for self-paced learning. They note that videos, when used appropriately, can improve both learning outcomes and student satisfaction.

The integration of video analytics within video-based learning environments further enhances the potential of this method. Kim, Park, and Yoon (2018) explore how video learning analytics can help identify student engagement patterns and improve the instructional process. They demonstrate that video analytics, such as tracking pause and rewind behavior, can provide insights into how students interact with content and where they struggle, allowing instructors to intervene in real-time. McGowan et al. (2016) apply learning analytics to better understand K–12 learner behavior in online video-based learning environments. Their study reveals that learning analytics can offer valuable insights into learner engagement, highlighting behaviors such as frequent pauses or skipping sections, which signal areas where students may need additional support or where the content may be unclear. The role of video analytics in MOOCs is also discussed by Chatti et al. (2016), who examine how video analytics can measure and improve student engagement. The study highlights how real-time data on learner interaction can inform instructional adjustments, improving learning outcomes and student retention rates in large-scale online environments. Lastly, Abedi and Khan (2021) introduce a method for measuring engagement based on emotional responses to video content. By incorporating affective states into video analytics, they offer a more nuanced understanding of student engagement, which goes beyond mere interaction to include emotional engagement, further enhancing the potential for personalized instruction.

Overall, video-based learning combined with analytics provides significant advantages, such as enabling real-time feedback, identifying engagement patterns, and tailoring content to student needs. However, challenges remain, particularly in terms of interpreting data accurately and ensuring equitable access to the required technology for all learners.

2.2 Adaptive Learning with Multimedia Materials

Adaptive learning refers to educational systems that adjust the content, pace, and learning path according to individual learner needs. By integrating multimedia materials, such as videos, interactive quizzes, and simulations, adaptive learning systems can cater to a wide range of learning preferences and offer personalized learning experiences.

Woolf (2009) provides an in-depth look at intelligent tutoring systems (ITS) that adapt to student behavior. These systems monitor student performance and adjust the instructional content accordingly, offering a highly personalized learning experience. The use of multimedia materials within these systems enhances their effectiveness by providing varied and engaging content that can be tailored to the learner's needs. Coffield et al. (2004) explore the importance of learning styles in adaptive learning. The paper emphasizes that different learners have different preferences, and adaptive systems that incorporate multimedia can meet these diverse needs. By using videos, graphics, and text, multimedia-based adaptive learning systems can reach students with varying cognitive and sensory preferences, ensuring a more inclusive learning environment. The integration of multimedia materials in adaptive learning systems is also discussed by Webb and Doman (2008), who investigate the impact of multimedia in adaptive learning environments. Their study shows that multimedia can enhance engagement and learning outcomes by providing diverse content formats. However, they also note that effective integration of multimedia requires thoughtful design to ensure it aligns with pedagogical goals and enhances the learning experience. Dabbagh and Kitsantas (2012) focus on personal learning environments (PLEs) and how multimedia materials can support self-regulated learning. By providing students with the ability to choose and interact with various types of content (e.g., video, text, and simulations), PLEs allow learners to take control of their educational journey. This flexibility is a core feature of adaptive learning, enabling students to customize their learning paths according to their preferences and needs. Siemens

(2013) introduces the field of learning analytics and discusses its role in adaptive learning systems. Learning analytics allows educators to collect data on student interactions, which can then be used to inform instructional decisions. This data-driven approach is essential for the success of adaptive learning systems, as it enables real-time adjustments to learning paths based on student performance. Finally, Jovanović, Gašević, and Siemens (2017) examine the role of learning analytics in education, specifically in adaptive learning environments. The authors argue that learning analytics, when integrated with adaptive systems, can provide a deeper understanding of student progress and engagement. By analyzing data from multimedia materials, such as videos, instructors can make informed decisions about how to adjust content and teaching strategies, ultimately improving student learning outcomes.

In conclusion, adaptive learning systems that utilize multimedia materials offer a promising approach to personalized education. The ability to cater to diverse learning preferences and adjust content based on real-time data allows for a more effective and engaging learning experience. However, successful implementation requires careful consideration of instructional design, technology access, and teacher support to ensure the systems meet the needs of all learners.

2.3 Summary

The integration of video-based learning with learning analytics provides an innovative approach to understanding and improving student engagement. Studies show that video analytics can track learner behavior in real-time, enabling instructors to adjust content and teaching methods to better support students. Meanwhile, adaptive learning systems enhanced by multimedia materials offer the potential to personalize education, improving engagement and learning outcomes by tailoring content to individual needs. Both approaches hold significant promise, but challenges such as technology literacy, data interpretation, and integration with existing teaching frameworks should be addressed for them to be fully effective, especially in developing countries like Thailand. Further research and development are needed to explore the practical application of these systems in diverse educational contexts and to ensure equitable access to personalized learning experiences.

3. Video-Based Learning and Video Analytics Tool

The video-based learning tool developed for this study was designed to support adaptive learning and integrated learning analytics. An overview of the tool is sketched in Figure 1.

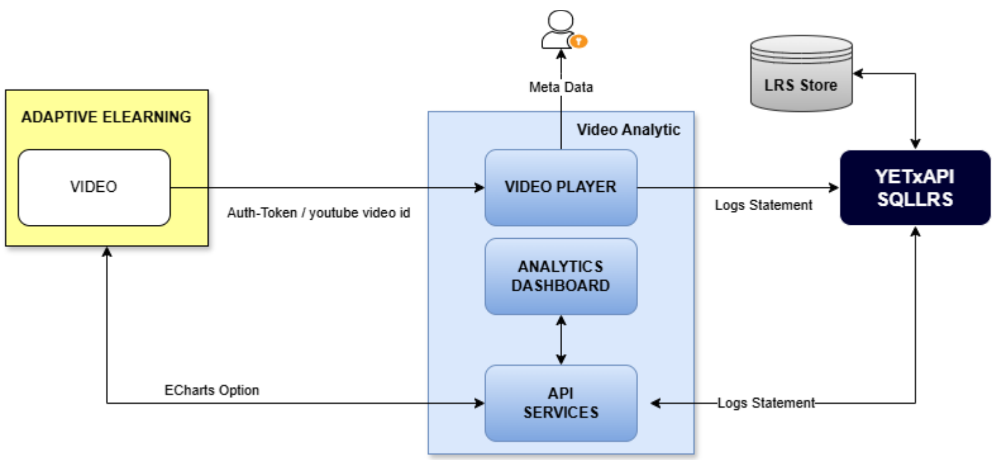

Figure 1. An overview of the video analytics supporting tool.

The Adaptive eLearning system integrates a powerful Video Analytic module to support personalized learning by monitoring how students interact with video content. When a learner starts a lesson, the system sends an authentication token or a YouTube video ID to the Video Analytic system through a secure API. The video is then loaded using the YouTube IFrame API, which allows precise control over playback using JavaScript. While the video plays, the system gathers student metadata—such as user ID and login time—and links it to real-time interaction data. It tracks key behaviors including pauses, skips, rewinds, and total watch time. These actions are recorded as structured JSON statements following the Experience API (xAPI) standard, which allows learning activities to be tracked across different systems.

The interaction data is stored in a Learning Record Store (LRS), such as YET xAPI or SQLLRS, which acts as a centralized database of learner activity. An API service then retrieves this data and presents it through an Analytics Dashboard. This dashboard visualizes the data using tools like ECharts to show key metrics—such as how often learners pause, how much time they rewind, or which parts they skip. These insights help instructors understand student engagement and make data-informed decisions. They can revise content pacing, identify confusing sections, and design more effective adaptive learning paths based on actual student behavior. The system ultimately supports a smarter, more responsive teaching approach tailored to each learner's needs.

3.1 Video Content

The video-based learning platform used in this study is designed to support both public and private instructional videos. Public videos are provided by higher-level organizations and are accessible to all students across schools. In contrast, private videos are created by individual instructors to meet the specific needs of their classrooms. Preferably, video content should be segmented into parts such as introduction, main content, demo or applicable content (if have), and conclusion. Each course includes one or more subjects, and each subject consists of 5 to 8 lesson videos. Students are assigned to watch videos within their enrolled course but are also allowed to explore other videos freely on the platform. Each video entry is tagged with the uploader's identity along with the exact timestamp of upload. This allows the system to distinguish between centrally distributed content and instructor-generated materials, and to track the freshness and relevance of videos accessed by students over time. To maintain content traceability, the system supports version control for video uploads. Instructors may update videos, with each new version logged under the same video ID but with a new version number and updated timestamp. This enables analysis of engagement across different content iterations. Thus, we design video metadata as given in Table 1.

Table 1. Video Metadata

Field Name	**Data Type**	**Description**
video_id	VARCHAR	Unique identifier for the video (same ID used across versions)
version_number	INT	Indicates the version of the video, starting from 1
subject_id	VARCHAR	Foreign key linking to the subject this video belongs to
lesson_number	INT	Order of the lesson within the subject
video_type	ENUM	Type of video: public or private
uploader_id	VARCHAR	ID of the person or organization that uploaded the video
upload_timestamp	DATETIME	Timestamp when the video was first uploaded
last_updated	DATETIME	Timestamp when the video was last updated
duration_seconds	INT	Total length of the video in seconds
status	ENUM	active, archived, or replaced (to handle deprecated versions)
description	TEXT	Optional description of the video
title	TEXT	Title of the video

3.2 Video Analytics Integration

To evaluate student engagement and behavior, the system records a range of data during video sessions. Each video is tagged with metadata, including its type (public or private), the associated course, subject, and lesson number. For every viewing session, the platform logs the student ID, the type of viewing (whether assigned or exploratory), and session duration. In addition, detailed interaction logs are collected, capturing events such as play, pause, seek, rewind, and skip, along with corresponding timestamps and video playback positions.

To enhance adaptive learning and provide personalized support, the system collects detailed video interaction data to enable in-depth video analytics. These analytics help to understand student engagement patterns, identify difficulties, and adapt learning pathways accordingly. This study uses a YouTube-style video player integrated via the YouTube IFrame API. The system captures rich interaction data during each viewing session, such as when students play, pause, seek backward or forward, and stop the video. By analyzing these behaviors, the platform can infer levels of attention, comprehension, and pacing preferences.

Each viewing attempt is recorded as a unique session, capturing all interactions and timing information from the moment the student starts watching until they stop. Because students may pause and return later to continue, the system supports multiple sessions per video for each student. To facilitate personalized pacing, the system tracks the last watched position and allows resuming videos from that point, ensuring continuity in learning across sessions. The video interaction metadata is collected as given in Table 2.

Table 2. Video Interaction Metadata

Field Name	Data Type	Description
session_id	VARCHAR	Unique identifier for each video viewing session
student_id	VARCHAR	Unique identifier for the student
video_id	VARCHAR	Identifier for the video being viewed
version_number	INT	Version number of the video (in case of updates or multiple uploads)
session_start_time	DATETIME	Timestamp when the video session started
session_end_time	DATETIME	Timestamp when the video session ended
total_watch_time	INT	Total seconds the video was actively watched during the session
completion_rate	FLOAT	Fraction of the video watched in this session (0.0 to 1.0)
pause_count	INT	Number of times the video was paused
total_pause_duration	INT	Total duration in seconds the video was paused
rewind_count	INT	Number of times the video was rewound
total_rewind_duration	INT	Total seconds rewound during the session
forward_skip_count	INT	Number of times the video was skipped forward
total_forward_duration	INT	Total seconds skipped forward
resume_from_second	INT	Timestamp (in seconds) where the session started within the video if resuming from previous session
watch_events	JSON	Timestamped list of interaction events such as play, pause, seek, with playback timepoints

By analyzing pause frequency and duration, rewind events, and skip behavior, the system can identify segments that cause confusion or loss of interest. Total watch time and completion rates provide overall engagement metrics. Combining data from multiple sessions reveals students' pacing preferences and learning habits over time. These insights should enable the adaptive learning platform to provide timely support, suggest review materials, and personalize the learning experience for each student.

3.3 Behavior-driven Adaptivity Mechanism

To support adaptive learning in a video-based environment, the system collects and analyzes fine-grained playback behaviors such as rewinding, pausing, skipping forward, and total watch time. These behaviors act as proxies for cognitive engagement, confusion, or disengagement. For example, repeated pauses or rewinds at certain timestamps may signal areas where learners struggle to comprehend the material, while frequent skipping may indicate a lack of interest or a mismatch between content pacing and student readiness. Rather than relying on formal assessments, the system interprets these behaviors to deliver targeted recommendations and pacing feedback. This approach enables learners to receive support tailored to their interaction patterns, helping them manage their learning more effectively and promoting deeper engagement with the material.

To enhance the responsiveness of the video-based learning system, two adaptive mechanisms were designed based on behavioral data collected during video playback: (1) Segment-Level Recommendations and (2) Dynamic Pacing Feedback. These mechanisms aim to support learners through real-time interaction patterns without relying on traditional assessments.

- *The Segment-Level Recommendations* feature analyzes student interactions such as rewind frequency and pause patterns to detect moments of potential cognitive difficulty. When multiple rewind or pause events are clustered within a specific video segment, the system interprets this as an indication that the student may have struggled with the content. These flagged segments are then used to generate personalized prompts at the end of the session. The prompt is “Would you like a simplified explanation or summary of this part or to leave a question to instructor?” In case of requesting explanation, system will provide the short note from the instructor regarding the segment content. For leaving a question, assigned instructor may choose to write an answer to explain the part or arrange a facetime to provide verbal explanation. This feature allows students to direct their review toward specific content they or their classmates found challenging, enhancing comprehension without requiring teacher intervention.
- *The Dynamic Pacing Feedback mechanism* focuses on how students manage their viewing time across lesson videos. By analyzing metrics such as total watch time, completion rate, and skip patterns, the system classifies pacing behaviors, such as rapid skipping, incomplete viewing, or balanced engagement. If a student skips large portions of a video or completes it significantly faster than expected, the system generates reflective prompts to encourage deeper engagement. For instance, a message such as “You skipped 40% of this lesson. Consider reviewing it more thoroughly before continuing.” may be shown. This feedback encourages students to reflect on their learning pace and adjust their behavior accordingly. When unusual pacing persists across multiple videos, the system can flag this pattern for potential instructor attention or adjust learning timeline expectations in future recommendations.

Together, these two adaptive mechanisms leverage naturally occurring behavioral data to provide timely, non-intrusive support. They promote metacognitive awareness, personalized content engagement, and improved pacing, which are essential components of effective self-directed learning in video-based environments.

4. Experiments

4.1 Behavior-driven Adaptivity Mechanism

We aim to analyze the behavior of students during video-based learning regarding interaction data. Participants in this study consisted of Grade 14 students (Mattayom 4) from two different schools. The total of participants were 127 students. As part of their school assignments, all students were required to watch two educational videos related to artificial intelligence (AI) under supervision of their class instructor. The videos were assigned for students to watch in their free hours or after school. The first video, titled Introduction to Artificial Intelligence, had a total duration of 12 minutes and 25 seconds (745 seconds). The second video, titled AI Literacy, was 15 minutes and 7 seconds (907 seconds). Both videos were designed to introduce fundamental concepts of AI and promote digital literacy. Students accessed and watched these videos through an online learning platform, which automatically recorded various interaction metrics mentioned in Section 3.2 during playback, such as total watch time, number and duration of pauses, skips, and rewinds. The purpose was to analyze student engagement behavior during video consumption and its potential relationship with learning outcomes, as measured by a post-test with a maximum score of 5 points.

To better understand how students engaged with the learning content, participants were categorized as shown in Table 3.

Table 3. Categories of participants based on behavior

Category	**Description**	**Criteria**
Linear Viewers	Students who watched the video content from start to finish without substantial interaction.	no skipping, pausing less than thrice and total pause time is less than 60 seconds, no rewinding
Pausers	Students who made extensive use of the pause function.	pausing ≥ 3 times or total pausing duration ≥ 60 seconds
Skippers	Students who frequently skipped ahead in the video.	skipping ≥ 3 times or total skipping duration ≥ 50% of the video time
Rewinders	Students who primarily used the rewind function to revisit content.	rewinding ≥ 3 times or total rewinding duration ≥ 50% of the video time
Neutral Viewers	Students who made few interactions to the video but not extensive enough to belong to another category.	those do not belong to other category

The participants can be in several categories for pausers, skippers, and rewinders. However, those who belong to linear viewers and natural viewers cannot be in several categories.

4.2 Result

From all participants, the categories were assigned as shown in Figure 2. The post test score is then associated to the categories to represent their understanding of the content ae given in Table 4.

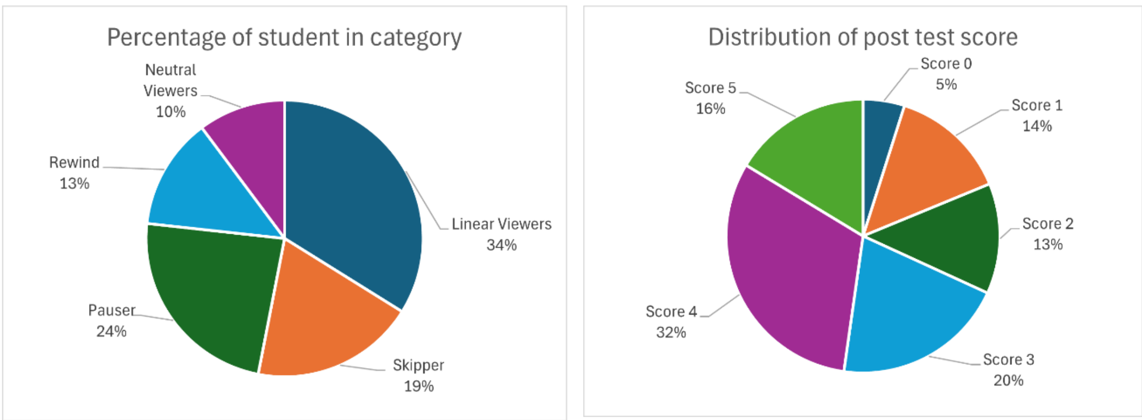

Figure 2. (Left) percentage of student in category and (Right) distribution of post test score

Table 4. Category of participants and post test score

Participant Category	**AVG**	**SD**
Linear Viewers	3.12	1.11
Neutral Viewers	3.24	1.63
Pausers	3.66	0.97
Skippers	1.91	1.60
Rewinders	4.38	0.79

From the post-test performance across categorized interaction behaviors, we learned the followings. Among the participant groups, *Rewinders*, who frequently revisited portions of the video or spent over half the time rewatching segments, achieved the highest average score (M = 4.38, SD = 0.79), indicating that repeated exposure to content may support comprehension and retention. Similarly, *Pausers*, who engaged with the video by pausing frequently or for extended durations, also demonstrated strong performance (M = 3.66, SD = 0.97), suggesting that reflective engagement may enhance learning. Neutral Viewers, defined as those who did not excessively interact with specific behavior, achieved a moderate mean score (M = 3.24, SD = 1.63), while Linear Viewers, who watched the content passively without interaction, had a slightly lower average score (M = 3.12, SD = 1.11). The Skippers group, characterized by skipping more than half of the video or engaging in frequent skipping, recorded the lowest average score (M = 1.91, SD = 1.60), highlighting a potential disengagement or lack of content exposure as a contributing factor to reduced comprehension. These findings suggest that deliberate and cognitively engaged forms of interactivity, such as pausing and rewinding, are associated with more favorable learning outcomes in video-based learning. In contrast, less engaged behaviors including skipping large parts of the video lead to lower understanding of the content.

By further analysis of the pattern of video watching behavior and interview with the responsible instructors, we examined how students engaged with the videos. Interestingly, not all students in the Pauser and Skipper groups fit neatly into a single behavioral pattern. For instance, among the Pausers, some students paused frequently or for long periods, but that did not always signal a lack of focus. When we examined deeper, we found that students who paused between 3 to 5 times and kept each pause under 2 minutes tended to score well on the post-test (average score of 4.2). These pauses likely reflected active learning behaviors, inclduing stopping to take notes or think something through. On the other hand, students who paused for more than 5 minutes were likely interrupted. These interruptions seemed to fall into two categories: external (like household distractions, phone notifications, or environmental noise) and internal (difficulty concentrating without the presence of peers or a teacher). Among the Pausers, about 12% appeared to be using the pause function for learning, while 41% likely paused due to disruptions. In the Skipper group, we found two very different patterns. Most (31 out of 45) scored poorly (0-2) on the post-test, likely because they were not engaged in video-based learning. However, a smaller group (10 students) were found to achieve good score (4-5), suggesting they may have skipped content they already understood. For the low scorers, skipping might have been a sign of disinterest. This could reflect a broader issue with motivation, or simply a mismatch between the video format and how they prefer to learn. Some students may find lecture-style videos dull, especially if they are used to more dynamic or interactive content like TikTok, video games, or social platforms.

5. Conclusion

This paper presents a video-based learning system with learning analytics for detailed tracking of Thai learner behavior. The log is designed to detect interactions that learner do while watching the educational video including pausing, skipping, and rewinding. Then the interactions and their timestamps are calculated into count and duration of each interaction. The system also includes an adaptive mechanism that provide extra prompt for students to connect to instructors for feedback or suggest for other methods to improve understanding when they rush through content.

From experiment results, we are able to identify behavioral trends as linear viewers, pausers, skippers, rewinders, and neutral viewers based on students' interaction patterns. Pausers, particularly those who paused briefly and frequently, achieved higher average post-test scores, suggesting that thoughtful, active engagement like reflection or notetaking contributes positively to understanding. Rewinders performed the best among all groups to achieve 4.38 average post test score, indicating the value of reviewing difficult content. On the other hand, students who skipped more than half of the video typically scored lowest as 1.91

average post test score, although there are a few high-performing skippers who have prior knowledge and choose to skip the known content.

For future work, we plan to implement more adaptive mechanism in two directions. First is adaptivity towards personalized content matching based on their behavior and preference. Second is to add more learning functions such as chatbot to provide live question-answering regarding the learning content or augmented reality to demonstrate the objects in 3-dimension.

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