WIP: Understanding Students' In-Video Dropout Behavior in Large Online Math Learning Platform

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***Abstract*—This work-in-progress research paper aims to explore students' dropout behavior during video engagement in online learning platforms. As online learning becomes increasingly popular, analyzing how students engage with video content provides important insights into their learning behaviors. This study explores multiple factors influencing K-12 students' in-video dropout rates in online math education. We examined 34,666,481 log entries from Math Nation, covering 1313 videos and 14,251 students. Using survival analysis, we evaluated how 27 variables, including demographic details, video interaction behaviors, and video characteristics(e.g. length, category), affect in-video dropout. Our findings reveal that video length significantly predicts dropout, with each additional minute increasing the dropout rate by 1.26%. Videos with higher dropout rates often feature more frequent pauses, jumps, and rewatches. The study also highlights that the quality of video content, the creators of the videos, and how students interact with the videos are crucial factors affecting dropout rates. Further research is needed to determine the specific causes of video dropout.**

***Index Terms*—in-video dropout, survival analysis, video learning**

I. Introduction

Online learning has become increasingly popular for both K-12 education and higher education. This is because it has the ability to reach a wider audience, offer self-paced learning opportunities, and provide engaging multimedia resources for students [1; 2]. Instructional videos are a common type of multimedia learning material used in online learning environments to enhance students' understanding, engagement, and retention of complex concepts. Lecture or tutorial videos offer numerous benefits, such as supporting effective knowledge acquisition [3], increasing students' interest and motivation [4], and promoting engaging and interactive learning experiences [5; 6].

In-video dropout has been the subject of interest to many researchers in the field due to its criticality. Studies have explored in-video dropout at various levels. Some of these studies focused on the characteristics of the video, such as its length and complexity [7]. The results of these studies showed that longer videos tend to reduce students' engagement while increasing the likelihood of in-video dropout [8]. Other studies analyzed the relationship between the instructors' delivery methods and the occurrence of in-video dropout. For instance, studies investigated how interactive the instruction is [9]. These studies found that the more interactive the instructions were, the more engaging the videos would be, indicated by the presentation style [10] and lexical and syntactic use of language by the instructor [11], and the less likely in-video dropout would happen [12]. Lastly, numerous studies have examined learners' video interactions in relation to in-video dropout [11; 13].

Previous research has highlighted the significance of various factors that impact in-video dropouts at different levels, including student-level, video-level, or tutor-level. However, most studies tend to focus only on a single level, such as analyzing video-level factors like video lengths [8] or student-level factors like student-video interaction clickstreams [11; 13; 14]. In order to gain a more comprehensive understanding of what influences in-video dropouts, it is important to integrate multiple levels of factors in the analysis to compare their relative importance. Besides, while most previous studies have focused on higher education [7; 12; 13], research on in-video dropouts in K-12 settings is limited. Furthermore, although some researchers [13] have attempted manual content analysis to identify potential reasons for peaks within videos, limited attention has been paid to the qualitative content analysis of in-video dropouts. Motivated by this, we aim to adopt a mixed method for the in-video dropout analysis.

We utilized a large dataset of 34,666,481 log entries left by 14,251 students in a secondary school video-based online learning platform, Math Nation[1]. Based on the previous literature, we first drew possible factors that could influence students' in-video dropouts at different levels. Then, we mapped the log data points with factors at each level, including student, video, tutor, and session level. This study investigated these multi-level factors that possibly impact students' in-video dropout using survival analysis. For the next step, we will conduct a qualitative analysis of the content of the videos where dropout occurs. The study aims to answer two research questions (RQs):

- RQ1. What influences student dropouts during online math video sessions?
- RQ2. What are the possible reasons of students' in-video dropouts in online math learning?

[1] https://www.mathnation.com/

II. Methods

A. Research data and context

Data for this study was sourced from Math Nation, an online platform for mathematics learning and tutoring. The platform is widely used by over a million secondary school students and teachers across the United States. The data analyzed ranged from May 1st 2017 to December 31 2019. We extracted data related to students' learning characteristics, video characteristics, tutors' characteristics, and the interaction between students and videos. We selected 34,666,481 log entries related to student video-watching activities and other behavior tracks. The logs encompassed 1,313 videos and 14,251 students. This data collection were approved by the Institutional Review Board of our institute (No.IRB202201770).

B. Variable selection and computation

We analyzed students' in-video dropout using various variables. Demographic data, student-level variables, video-level variables, tutor-level variables, and session-level variables were included in the analysis. Beyond demographic data, we included 11 variables about students' learning performance and behavior under the student-level category. The video-level variables included six variables about the videos, such as their duration (*length*), category (*videoCategory*). We also analyzed the peaks of rewatch (*rewatchPeaks*), pause (*pausePeaks*), and jump (*seekPeaks*) interactions across all videos to identify moments of increased interest or potential confusion based on previous study [7; 13]. The four tutor-level variables included the tutor's gender, speech rate, and whether their demographic matched that of the student (*sameDemo*). This variable was selected based on prior research indicating that students are more engaged when instructed by teachers from similar demographic groups, as this can foster role-modeling and inclusiveness [15; 16]. Finally, the three session-level variables included information about whether a session involved a student rewatching a video (*rewatchVideo*), the last action the student took before dropping off the video (*actionBeforeDrop*) and whether the student watch the video before a test (*beforeTest*).

C. Data cleaning and processing

To ensure consistency and comparability in our analysis, we excluded videos that were exceptionally short (shorter than 1 minute) or long (longer than 40 minutes) in the initial dataset, ultimately obtaining a total of 1,197 videos. Additionally, motivated by [17], we processed the different types of variables in Table I; binary variables [2] were encoded as 0 or 1. For ordinal variables, we represented the levels of the variable in ascending order to reflect the increase in level. For numerical variables, we standardized them. To facilitate model interpretation, we applied dummy coding to nominal variables *videoTutor* and *actionBeforeDrop*, with *videoTutor* ID *1* serving as the reference category for *videoTutor*, and *completed* as the reference category for *actionBeforeDrop*.

[2] In this study, gender and race were considered as binary variables to simplify the analysis.

D. Survival analysis

Survival analysis is a statistical technique that examines the duration of time until a specific event of interest occurs [18]. In previous studies, survival analysis has been utilized to investigate patterns of student and teacher usage that contribute to student dropout rates in online learning platforms [19]. Additionally, it has been used to identify the factors that influence the length of time users participate in online professional learning communities [20]. In our research, we employed a survival model to examine which factors impact the occurrence of in-video dropouts among secondary school students on online math learning platforms. Each session included variables presented in Table I and an in-video dropout event indicator. The indicator was set to 1 if a student dropped out of the video before it reached 90% completion, and 0 if the student either completed the video or watched at least 90% of it, thereby not exhibiting in-video dropout behavior. We selected 90% as our threshold for two reasons. First, previous research has indicated that many videos did not include any video interactions during the last 10% of their length [21]. Second, the videos on Math Nation usually include an ending video animation that is not relevant to the complete content of the video. Within the log data, the first timestamp (minimum timestamp) for a specific video represents the start time of the student viewing that video. The last timestamp (maximum timestamp) represents the time the student dropped out of the video. The duration from the start to the exit is known as the survival time. The application of survival analysis in this research is crucial for understanding the factors that contribute to students' in-video dropouts. We utilized the Cox proportional hazards model [22] to explore these factors and in-video dropout behavior.

III. Preliminary Results & Discussion

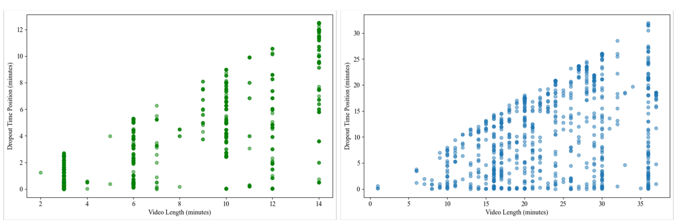
A. Video-level Variables Analysis

To analyze the impact of video types on student in-video dropout, we categorized the videos into two categories (i.e., lecture videos and tutorial videos) and visualized the specific time points of student dropouts while watching videos of different types in scatter plots (for readability, we sampled 1,000 sessions in tutorial videos and lecture videos, respectively). In Figure 1 (a) and (b), the x-axis represents the total length of a video, and the y-axis represents the specific time point of student dropout, where each point represents a session of video watching. A point in Figure 1 (a) represents a session where a student watches a tutorial video, whereas a point in Figure 1 (b) indicates a session where a student watches a lecture video. For the tutorial videos, the average duration is 4.67 minutes, for lecture videos, it is 18.37 minutes.

We further calculated each video's dropout rate and visualized the video dropout rate for the rewatch compared to the first-time watch sessions. The blue points in Figure 2 represent rewatch sessions, while the orange points indicate first-time watch sessions. For the videos that students rewatch, the dropout rate is almost 100%. For first-time-watch sessions,

TABLE I
VARIABLES SELECTED FOR ANALYSIS.

Category	Name	Description	Type
Student's demographic	gender	Students' gender	Binary
	race	Students' race	Binary
	frl	Whether a student is in the free and reduced lunch program	Binary
Student-level	achievementLevel	Students' performance level	Ordinal
	totalNumberofAbsences	Students' absence times from classes	Numerical
	sessionSum	The sum of session students have in this period	Numerical
	totalQuizItems	The sum of questions students solved in this period	Numerical
	documentView	Times students review the video documents	Numerical
	topicVideoView	Topic videos students reviewed	Numerical
	tutorialVideoView	Tutorial videos students reviewed	Numerical
	videoCompletedSum	The sum of video students have completed watch in this period	Numerical
	videoPauseSum	The sum of students click pause	Numerical
	videoPlaySum	The sum of students click play	Numerical
	videoSeekSum	Times students jump in videos	Numerical
Video-level	length	Video time length	Numerical
	videoCategory	The content of the Video, 0 represents tutorial or 1 represents lecture	Binary
	videoSumRewatch	The sum of all the rewatch in a video from all sessions	Numerical
	rewatchPeaks	The detected rewatch peaks in a video	Numerical
	pausePeaks	The detected pause peaks in a video	Numerical
	seekPeaks	The detected seek peaks in a video	Numerical
Tutor-level	tutorGender	The gender of the tutor	Binary
	tutorInDepthRank	The depth of the tutor's explanations	Ordinal
	sameDemo	Whether the demographic (gender) of the student match the video tutor	Binary
	videoTutor	The tutor who created the video	Nominal
Session-level	rewatchVideo	Whether student is rewatching this video or not	Binary
	actionBeforeDrop	The last action before the student dropout	Nominal
	beforeTest	Whether the session is watching a video before a quiz	Binary



(a) Tutorial video sessions (b) Lecture Video Sessions

Fig. 1. Video dropout rate on different video categories and different lengths.

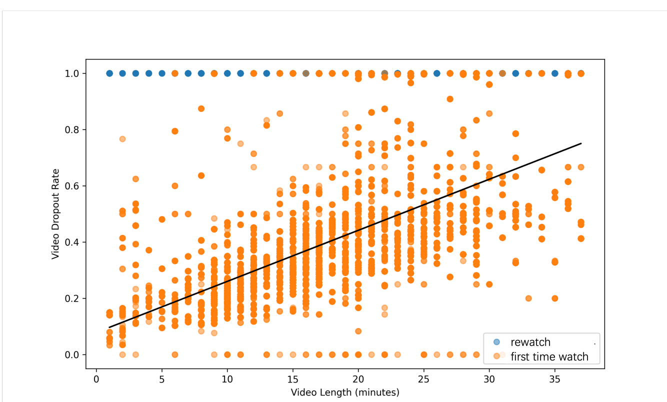


Fig. 2. Video dropout rate on different video duration.

dropout rates increase with the videos' duration, it indicates that longer videos usually have higher video dropout rates.

TABLE II
DROPOUT RATE WITH AVERAGE DIFFERENT ACTION PEAKS.

Dropout rate level	rewatchPeaks	pausePeaks	seekPeaks	Ave. duration (min)
High	7.44	7.33	7.19	22.85
Medium	6.66	6.52	6.30	19.98
Low	4.67	4.61	4.50	12.74

For first time watch videos, linear regression shows that video length is a significant predictor of the video's dropout rate ($R^2 = 0.81, F(1, 1196) = 430.6, p < 0.001$). With each additional minute of video length increasing the dropout rate by an average of 1.26%. As shown in Table II, we categorized all videos into three levels based on their dropout rates: high (dropout rate is higher than 0.66), medium (dropout rate is higher than 0.33 but lower than 0.66), and low (dropout rate is lower than 0.33). We then counted the number of peaks for the videos in each category and found that videos with higher dropout rates tend to have more peaks.

B. Survival Analysis Results & Discussion

First, at the student level, we explored how traits such as academic performance, engagement in learning activities, and styles of video interaction impact dropout rates. We discovered that higher academic achievements (noted as *achievementLevel*) are associated with a lower risk of dropout (HR $= 0.96; p < 0.005$); an increase by one level in academic achievement could reduce the likelihood of in-video dropout by 4%. This indicates that students with better

TABLE III

RESULTS OF THE SURVIVAL MODEL.

Category	Variables	HR (SE)	[95% CI]
	gender	1.05 (0.01)***	[1.03,1.07]
	race	1.05 (0.01)***	[1.02,1.07]
Student's Demographic	frl	1.07 (0.01)***	[1.05,1.09]
	achievementLevel	0.96 (0.00)***	[0.96,0.97]
	totalNumberofAbsences	1.00 (0.00)	[0.99,1.01]
	sessionSum	1.01 (0.01)***	[1.00,1.03]
	videoCompletedSum	0.99 (0.01)	[0.98,1.00]
	videoPauseSum	0.98 (0.01)***	[0.97,0.99]
	videoPlaySum	0.98 (0.01)**	[0.97,0.99]
	videoSeekSum	0.94 (0.00)***	[0.93,0.95]
	totalQuestions	1.01 (0.00)	[1.00,1.01]
	documentView	1.01 (0.00)*	[1.00,1.02]
	solutionVideoView	0.99 (0.00)***	[0.98,1.00]
Student-level	topicVideoView	1.02 (0.00)***	[1.01,1.03]
Video-level	length	1.17 (0.01)***	[1.16,1.19]
	videoCategory	1.27 (0.04)***	[1.18,1.37]
	videoTutor_2	1.07 (0.02)***	[1.04,1.11]
	videoTutor_3	1.09 (0.02)***	[1.05,1.12]
	videoTutor_4	0.59 (0.32)	[0.32,1.10]
	videoTutor_5	0.83 (0.02)***	[0.81,0.86]
	videoTutor_6	1.00 (0.02)	[0.96,1.05]
	videoTutor_7	0.97 (0.23)	[0.61,1.52]
	videoTutor_8	0.96 (0.02)*	[0.93,1.00]
	videoSumRewatch	0.98 (0.01)***	[0.97,0.99]
	rewatchPeaks	0.87 (0.01)***	[0.86,0.89]
	pausePeaks	0.73 (0.01)***	[0.72,0.74]
	seekPeaks	0.88 (0.01)***	[0.87,0.89]
	tutorGender	0.94 (0.01)***	[0.91,0.97]
Tutor-level	tutorSpeedRank	1.01 (0.00)***	[1.01,1.02]
Session-level	rewatchVideo	1.18 (0.01)***	[1.16,1.21]
	actionBeforeDrop_playing	1.60 (0.01)***	[1.56,1.64]
	actionBeforeDrop_seek	1.20 (0.02)***	[1.16,1.23]
	actionBeforeDrop_pause	1.42 (0.01)***	[1.38,1.47]
	actionBeforeDrop_play	1.06 (0.05)	[0.97,1.16]
	beforeTest	1.23 (0.01)***	[1.20,1.25]
	sameDemo	1.00 (0.01)	[0.99,1.02]
	concordance	0.76	
	partial AIC	972684.44	
	BIC	973035.00	

Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.005$. The Hazard Ratio (HR) is a measure that compares the risk of an event occurring in one group/condition to another. An HR greater than 1 indicates that as the variable value increases, the dropout risk also increases. The concordance value (0.76) indicates that the model has a good fit, with a partial AIC value of 972684 and a BIC value of 973035 (last three rows).

academic records tend to complete instructional videos more frequently. In terms of engagement, factors like *sessionSum* (HR $= 1.02; p < 0.005$) and *topicVideoView* (HR $= 1.02; p < 0.005$) significantly affect the dropout rates. For instance, each additional session attended increases the dropout rate by 2%, suggesting a higher tendency to dropout as students engage more frequently on the platform. Watching more topic-related videos also raises the likelihood of dropping out by 2%, while each additional tutorial video watched reduces this risk by 1% (HR $= 0.99; p < 0.05$). Additionally, engagement metrics like *videoCompletedSum* (HR $= 0.95; p < 0.005$), *videoPlaySum* (HR $= 0.98; p < 0.05$), and *videoSeekSum* (HR $= 0.95; p < 0.005$) show that more interactive behaviors with videos correlate with reduced dropout risks. Each extra video completed, played, or searched through decreases the dropout risk by 5%, 2%, and 5%, respectively.

Secondly, video-level variables such as video length, category, and viewing patterns significantly influence student dropout rates. For instance, an increase in video length by one unit (which is 7.51 minutes in this study) corresponds to a 17% increase in dropout risk (HR $= 1.17; p < 0.005$). This supports previous findings that longer videos tend to have higher dropout rates [7; 13]. Unlike earlier studies suggesting peak engagement at much shorter intervals in higher education [7; 8], our findings indicate that secondary school students engaged with Math Nation as part of their curriculum tend to stay engaged for longer periods. Regarding video categories, students show a 27% higher dropout rate in lecture videos compared to tutorial videos (HR $= 1.27; p < 0.005$). This outcome seems to contradict the findings reported by [13], which suggested higher dropout rates in tutorial videos than in lecture videos. This discrepancy could stem from the longer average duration of lecture videos (18.37 minutes) in our dataset, relative to tutorial videos (4.67 minutes). Consistently, Fig. 1 reveals that tutorial videos typically last no more than 15 minutes, whereas lecture videos generally exceed 5 minutes, with some lasting over 35 minutes. When the video durations are comparable, tutorial videos experience higher student dropouts in the middle to later segments (e.g., tutorials of 10 and 14 minutes as shown in Fig. 1 (a)).

For tutor-level variables, we analyzed tutors' demographic traits (*tutorGender*) and teaching styles (*tutorInDepthRank*), along with the match between student and tutor demographics (*sameDemo*). We also examined the individual impact of tutors on in-video dropouts. Both *tutorGender* (HR $= 0.94$, $p < 0.005$) and *tutorInDepthRank* (HR $= 1.01$, $p < 0.005$) significantly affect student dropout rates. Statistically, videos from male tutors are associated with a 6% lower dropout risk compared to those from female tutors. This could relate to the higher number of videos from female tutors in the dataset. The depth of the tutor's teaching style seems to slightly increase the dropout risk; for each increase in teaching depth, the dropout risk may rise by 1%. This supports earlier findings that faster-paced instructional videos enhance student engagement [7]. Meanwhile, *sameDemo* showed no significant effect, possibly because we only included gender and not race, which has been identified as more crucial in literature concerning role-modeling effects [15] and inclusiveness [16].

The session-level variables cover students rewatching videos (*rewatchVideo*), their last actions before dropout (*actionBeforeDrop*), and if they took a quiz after the video (*beforeTest*). If a student rewatches a video, their dropout risk increases by nearly 18% compared to their first viewing (HR $= 1.18; p < 0.005$), supporting [13]'s findings that rewatching leads to a 30% higher dropout rate than initial viewing. Actions preceding dropout, including playing, seeking, and pausing, correlate with a heightened dropout risk, suggesting students often manipulate video controls before exiting. Notably, pausing before dropout (*actionBeforeDrop_pause*) significantly affects dropout rates the most (HR $= 1.42; p < 0.005$), indicating students likely pause the video before exiting. Moreover, the *beforeTest* variable reveals a 23% higher dropout rate when students take a quiz after watching a video compared to other conditions (HR $= 1.23; p < 0.005$), possibly because students may not watch the entire video but rather review specific parts to prepare for the quiz.

Conclusion & Future Work

This research aims to reveal multiple levels of factors that possibly impact students' in-video dropout behaviors in a secondary school video-based online math learning platform. The factors include student, video, tutor, and session levels. Students with higher achievement, more active participation in learning, and more interactive video-watching habits show less likelihood of dropping out of the videos. On the other hand, students who show more divergent learning patterns (e.g., watching more lecture videos on new topics) show a higher risk of dropping out of each video. Videos with longer duration and videos of lecture types (versus. tutorial videos) show a higher risk of dropouts, while videos with more clickstreams (i.e., rewatch, pause, seek) show less likelihood for students' dropout. In addition, in-depth videos where tutors speak slower and cases where students took a self-assessment quiz after watching the video yielded a higher dropout rate. The survival analysis identifies various factors influencing students' dropout behavior during video sessions. However, it does not uncover the specific reasons they discontinue watching. To explore these reasons concerning video content, we will perform a manual analysis of periods when in-video dropouts occur. In the future, we will select 100 videos recording the highest dropout rates. Subsequently, we will depict the dropout instances within these videos and further identify key factors potentially influencing dropout rates.

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