Modeling Trust Judgments in Educational Videos: An Exploratory Predictive Approach Integrating Navigation Behavior, Attitude, and Disposition to Critical Thinking

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Abstract. This study investigates how navigation behaviors, attitude, and critical thinking disposition predict trust attribution in educational videos among middle and high school students. Grounded in the hypothesis that epistemic judgments are shaped by a multidimensional interplay of cognitive, affective, and dispositional factors, we analyzed data collected from a video-based learning platform integrating selected videos and reflective questioning on controversial socio-scientific issues. Partial correlation analyses revealed significant associations between students' interaction patterns with the videos (e.g., seeking, pausing), attitude, and critical thinking disposition. Notably, a positive attitude about video content was negatively associated with critical thinking disposition, suggesting that students' positive perception about the topic may attenuate epistemic vigilance. Predictive modeling confirmed that including attitudinal and dispositional variables significantly improves the classification accuracy of normative trust judgments compared to models based on navigation traces alone. The Critical Thinking Disposition indicator (CTDI) proved to be a robust predictor of evaluative success.

Keywords: Critical thinking; Learning Analytics; Exploratory Study

1. Introduction and research context

The Internet and social media have significantly expanded access to educational resources for both students and teachers. While the abundance of online information offers vast learning opportunities, it also introduces challenges, such as misinformation and inaccuracies [18]. The ability to critically assess the trustworthiness of digital content has thus become essential. However, prior research indicates that students frequently struggle with these evaluation tasks [21].

While critical thinking has been extensively studied in textual contexts [22], its application to video-based learning remains underexplored [6]. Videos present unique cognitive challenges due to their multisensory nature—combining sound, image, and narrative—which can trigger affective heuristics that influence credibility assessments [19]. Emotions, far from being mere physiological reactions, increasingly appear to function as cognitive tools for evaluating content [12], serving as informational cues in epistemic judgment [23]. Such judgments are pivotal in determining trust in information and decisions about its use [20], and require a dual challenge: distinguishing credible claims and identifying reliable sources [16]. This process is also related to cognitive development: cognitive maturation significantly improves critical evaluation, with high school students outperforming middle school students in detecting reliable sources [1]. Moreover, critical thinking skills are not solely cognitive; they are also shaped by individual disposition [8]. Critical thinking disposition refers to an individual's tendency to critically analyze and evaluate information, ideas, or situations—often without deliberate awareness. These dispositions reflect a broader intellectual attitude characterized by curiosity, open-mindedness, and cognitive rigor, which fosters the spontaneous questioning of encountered information [10]. By shaping how learners conceptualize knowledge and the justification of knowledge, such dispositions influence how individuals engage with information [5] and directly impact judgments of credibility and source reliability [13]

These premises underscore the need for further research into how students critically engage with video content, particularly how affective, cognitive, and dispositional factors interact during epistemic judgments. Affective dimensions are receiving increasing attention in recent work [3, 7], and are often overlooked in learning analytics, since they are known to significantly impact learning outcomes [24]. In this work, we argue that the concept of attitude offers a particularly promising lens that could further inform this prior work. Commonly defined as a psychological tendency to evaluate an object with some degree of favor or disfavor, attitude inherently bridges both cognitive (e.g., prior beliefs) and affective components [2], and has repeatedly been shown to be a strong predictor of behavior [2]. Although well-established in psychology, attitude has mostly been studied in relation to usability, acceptability of digital platforms [26], or course satisfaction [27], rather than as a factor in epistemic evaluation. While prior research has emphasized the importance of dispositional variables in MOOC and LMS environments [25], to our knowledge, no studies have provided a comprehensive perspective on learners' attitude and critical thinking disposition—both of which are essential for critical thinking and trust evaluation. Furthermore, there is limited research in the field of learning analytics exploring the intersection between attitudinal dispositions and video-based learning environments [11].

This study contributes to filling this gap. It presents preliminary findings from Project [anonymised], which investigates how students' video interaction behaviors (e.g., play, pause), along with their attitudes (toward the video content) and critical thinking disposition, influence the quality of their epistemic judgments. The research is part of a broader initiative funded by the French Ministry of Education to develop an online learning platform for middle and high school students to promote critical video analysis skills. In this platform, students have access to learning sequences designed by teachers. These learning sequences integrate curated videos with reflective questioning about so, designed to help students critically evaluate both the speaker's expertise and the perceived credibility of the presented information. Specifically, we investigate how engagement patterns with the videos (e.g., pausing, seeking…), attitude, and critical thinking disposition can predict middle and high school learners' ability to construct their judgement of trust in educational videos. The originality of this exploratory study lies in its integration of psychological constructs—attitude and disposition to critical thinking—into predictive models of students' trust in video-based learning, with the aim of enriching our understanding of their validation strategies. Specifically, we address the following research questions:

- RQ1 – To what extent are students' navigation behaviors (e.g., pausing, seeking) associated with their attitude toward the video content and their disposition to critical thinking ?
- RQ2 – How do attitude, critical thinking disposition, navigation behaviors, and institutional context (e.g., type of school) influence the quality of students' trust judgments—that is, the degree to which their reported trust aligns with academic expectations ?
- RQ3 – Does a model combining students' video interactions, critical thinking disposition, and attitude predict success on academic evaluation task more accurately than a model based solely on navigation behaviors?

2 Data gathering and analytical methods

2.1. Data gathering

Data was collected from a cohort of students from 18 partner institutions (12 high schools and 7 middle schools). In total, data from 603 students were included in the analysis (398 middle schoolers and 205 high schoolers), comprising 302 girls (196 middle school, 107 high school), 292 boys (198 middle school, 95 high school), and 7 students who identified as "other" (4 middle school, 3 high school).

For this preliminary study, we only considered data from students' interaction with one learning sequence containing four videos available at the online platform developed for the project. These four videos were specifically designed to contrast speaker expertise (expert/non-expert) and perceived credibility of the information sources (good/bad information). After each video, students had to answer a question to assess how much they trusted the information provided in the video (judgement of trust). Details about the quality of information provided in each video, as well as the expertise level of the speaker is detailed in Table 1. All videos addressed the same overarching theme: *the potential dangers of screen time among young people*, and all advocated solely for the need to reduce that screen time. The following data was collected (see details in Table 2):

- **Attitude**. Before watching the videos, students indicated their baseline position on the need to reduce screen time using a 9-point Likert scale (1="strongly disagree" to 9="strongly agree"), providing a measure of their attitude about the video content.
- **Trust.** Each video was immediately followed by a trust judgement question in which students were asked to indicate how much trust they placed in the video on a 9-point Likert scale (1 = "I don't have any trust at all" to 9 = "I have complete trust").
- **Demographic variables.** The dataset further incorporates contextual demographic variables, including school type and self-reported gender. While institution type were included in the analyses to examine contextual effects on epistemic judgment, gender was used solely for descriptive purposes and was not tested as a predictive or explanatory variable in the present study.

- **Students' video-interaction traces**. These traces consist of a dataset of xAPI statements recorded on the project's dedicated platform [anonymised] from 37 sessions of the same activity. Each log entry includes a unique user account identifier, access time, video ID, session ID, event type (play, stop, pause, and seek), and the internal duration of the video. A play event is created when the user clicks the play button or moves to a particular position in the video. A pause event is generated when the user clicks the pause button. A seek event is triggered when the user navigates along the video timeline. Table 2 summarizes the information about the collected data.

Table 1. Description of the four study videos.

Video ID	Quality of Information Provided	Speaker Type
1	Poor	Expert
2	High-quality	Expert
3	High-quality	Non-expert
4	Poor	Non-expert

Table 2. Overview of collected data

Variable	Type	Use in Analysis
Attitude	Ordinal (9-point Likert scale)	Predictor
Trust	Ordinal (9-point Likert scale)	Outcome
School type	Categorical	Predictor
Gender	Categorical	-
Traces (video interaction)	Log data (xAPI statements : play, pause, seek, stop)	Predictor

2.2. Data pre-processing

We conducted the following data pre-processing (see Table 3 for summary). First, students' attitude was binarized (score above 5 = agreement, class 1; score below 5 = disagreement, class 0). For the video traces, and in line with previous work [11;12], we constructed our temporal sequences by dividing the videos into segments calibrated to 5-second intervals and counted the actions recorded during each period for every student. Specific navigation actions (forward and backward) were then computed using the same 5-second threshold, based on the difference in the video's internal duration between two consecutive seek events. If the difference represents a negative variation, it is labeled as a backward seek, and conversely, as a forward seek for positive variations. The threshold is adjusted to account for the normal progression of the video: a seek must exceed 5 seconds to be validated as a forward, corresponding at minimum to a jump of one temporal segment.

Table 3. Overview of calculated data

Variable	Type	Use in Analysis
Forward	Derived from Seek events showing a change in video time > 5s	Predictor
Backward	Derived from Seek events showing a change in video time < 5s	Predictor
bin_Att	Binarized from *Attitude* (1 = agreement [Attitude > 5], 0 = disagreement [Attitude < 5])	Predictor
ESC	Binary score computed from trust judgments on 4 videos	Predictor
CTDI	Score from 0 to 5 based on trust comparisons across video pairs	Predictor

Two distinct indicators were developed based on the trust judgments expressed by the participants, gathered from the judgement questions in the learning sequence. These two indicators are: (1) the Evaluative Success Criterion (ESC), aims to measure alignment with the expectations of an academic evaluation ; and (2) the Critical Thinking Disposition Indicator (CTDI), seeks to detect the disposition to critical thinking. The first indicator is situated within the framework of assessment, based on explicit criteria for validating information and assessing the authority of the speaker. From this perspective, students were expected to assign a trust rating strictly below 5 to videos conveying poor information (videos 1 and 4), and a trust rating strictly above 5 to videos conveying good information (videos 2 and 3). This binary evaluation enables identifying students who successfully applied the expected criteria in a school-based context. This situation exemplifies the dual skill set that students are expected to master by the end of high school: distinguishing credible information by recognizing source quality as a mediating factor (e.g., avoiding the pitfall of trusting "pseudo-experts"). The construction of this indicator is presented in Table 4. For the purposes of our modeling, this indicator was converted into a binary variable (class threshold: mean score).

Table 4. Construction of the evaluative success criterion (ESC).

Video ID	Criterion for Evaluative Success	Role
1	Trust < 5	Expected rejection (1pt)
2	Trust > 5	Expected validation (1pt)
3	Trust > 5	Expected validation (1pt)
4	Trust < 5	Expected rejection (1pt)

Nevertheless, this purely evaluative approach has one important limitation: it does not take into account the underlying dimensions of learning critical thinking, particularly the implicit representations students may develop regarding expertise, credibility, or the construction of knowledge [17]. To address this limitation, a second indicator was developed: the Critical Thinking Disposition Indicator (CTDI). This indicator is based on the relative comparison of judgments between videos, considering critical thinking disposition as a transversal cognitive process. For instance, a student may fail the formal evaluation while still demonstrating meaningful disposition to critical analysis criteria—for example, by assigning a higher level of trust to video 2 (expert, reliable information) than to video 3 (non-expert, reliable information), and more trust to video 1 (expert, unreliable information) than to video 4 (non-expert, unreliable information). This comparative reasoning reflects an ability to integrate speaker expertise as a factor of evaluation, regardless of the truthfulness of the information, and thus serves as a valuable indicator of learning progression. The pairing of relative judgments across the two formative dimensions (source reliability and information credibility; see Table 3 for details) required counting the comparison between videos 3 and 2 twice. This is because video 2 represents the optimal choice recommended to students: a trustworthy source conveying credible information—requiring both accurate recognition of speaker expertise and proper assessment of information credibility.

Table 5. Construction of the Critical Thinking Disposition Indicator (CTDI).

CTDI (Expertise)	CTDI (Information)
(Trust) video 1 > (Trust) video 4: 1 point	(Trust) video 4 < (Trust) video 3: 1 point
(Trust) video 2 > (Trust) video 3: 1 point	(Trust) video 1 < (Trust) video 3: 1 point
	(Trust) video 3 < (Trust) video 2: 1 point

2.3 Data analysis

To address the three research questions, we conducted a combination of partial correlation analyses and GLM (binomial, logit) regression modeling, using the Evaluative Success Criterion (ESC) as the primary outcome measure in predictive models.

RQ1 – Correlational analysis of behavioral, attitudinal and dispositional factors. To investigate how students' navigation behaviors relate to their attitude and critical thinking disposition, we computed partial correlations (Kendall's Tau) between these variables. This non-parametric method was selected due to the high number of tied ranks in the data, particularly on Likert-type scales. The correlation matrix included the following variables: *play, pause, seek, stop, forward, backward, bin_Att* and *CTDI*. Partial correlations were controlled for video ID and school type, in order to account for variance effects related to (1) the unique epistemic situation specific to each video (source credibility × information accuracy), and (2) developmental differences between educational contexts, to more precisely isolate the specific relationship between interaction variables [9].

RQ2 – Correlational analysis of normative epistemic judgment (ESC), behavioral, attitudinal, dispositional factors and School type. A similar set of partial correlation analyses (Kendall's Tau) was conducted to explore the relationship between the same variables listed above and the ESC outcome. However, in this case, school type was retained as a predictive variable (and not controlled for), to explicitly test its contribution to correct evaluation (given the forthcoming classification). Video ID remained a control variable.

RQ3 – GLM classification predicting ESC. To determine the predictive value of behavioral, attitudinal, dispositional, and contextual factors, we developed a series of GLM models (binomial family, link : logit), each using the ESC score as the dependent variable:

- Model 1 included all navigation behavior variables (captured and computed) and school type as predictors.
- Model 1b extended Model 1 by adding CTDI and bin_Att to account for students' critical thinking disposition and attitudinal stance.
- Model 2 included all predictors from Model 1b and added five interaction terms, selected on the basis of the significant partial correlations observed in RQ1 and RQ2 in line with our exploratory purpose (*CTDI*bin_Att + CTDI*seek + bin_Att*backward + bin_Att*seek + bin_Att*play*.).

Model 1 served as a baseline comparison between models focused on the improvement of predictive performance (e.g., accuracy, AIC) and the contribution of each additional variable or interaction. An important consideration in our modeling approach was the selection of an appropriate classification threshold to convert predicted probabilities into predicted categories. Rather than defaulting to the conventional 0.5 threshold, we optimized this parameter by identifying the point that maximized the trade-off between sensitivity and specificity, as proposed in prior work [4]. Given the observed imbalance in the dependent variable—with the majority of students meeting the ESC criteria —optimal classification thresholds were adjusted upward, ranging from 0.79 to 0.80 across models. This reflects the model's tendency to favor the dominant class and the need for stronger evidence to classify an instance as non-successful. This approach is particularly appropriate in cases of imbalanced data, or in contexts such as the interpretation of student learning processes, where false positives and false negatives may carry comparable implications.

3 Results

3.1 Association between navigation behaviors, attitude and critical thinking disposition (RQ1)

As shown in the table 6-A, the **CTDI showed a negative correlation with seeking behaviors** ($\tau = -0.019$, $p < .001$), indicating that **excessive seeking through the video timeline was related to weaker disposition**. However, attitude (bin_Att) showed significant, albeit weak, correlations with several navigation behaviors: it was negatively correlated with play ($\tau = -0.024$, $p < .001$) and positively with seek events ($\tau = 0.038$, $p < .001$) and backward navigation ($\tau = 0.015$, $p = .041$). These results suggest **that students with stronger agreement toward the video's message (in favor of screen time reduction) were more likely to rewatch segments of video,** potentially indicating a more active mode of viewing. Intercorrelations among navigation behaviors also revealed meaningful patterns: paused and seek behaviors were moderately negatively associated ($\tau = -0.163$, $p < .001$), while forward and backward movements were negatively related ($\tau = -0.136$, $p < .001$), supporting the existence of distinct navigation strategies—namely, progressive (forward) versus review-oriented (backward). These strategies appear mutually exclusive for most students.

3.2 Association between navigation behaviors, attitude, critical thinking disposition, school type and ESC (RQ2)

As shown in Table 6-B, the Critical Thinking Disposition indicator (CTDI) was significantly associated with the Evaluative Success Criterion (ESC) ($\tau = 0.280$, $p < .001$), suggesting that students who demonstrated disposition to the dimensions of critical analysis also tended to perform better on the normative "evaluation" task. ESC was also significantly correlated with several navigation behaviors. The ESC showed a negative correlation with seeking behaviors ($\tau = -0.019$, $p < .001$) and forward navigation ($\tau = –0.053$, $p < .001$), pointing to a detrimental effect of frequent or anticipatory seeking on the quality of epistemic judgment. However, ESC was positively correlated with paused events ($\tau = 0.018$, $p = 0.015$) and play events ($\tau = 0.024$, $p = .001$), suggesting that students who actively engaged with the video content (rather than skipping or scanning) were more likely to succeed in the evaluation task. Attitude (bin_Att) was not significantly associated with ESC ($\tau = –0.007$, $p = .329$), but was negatively associated with CTDI ($\tau = –0.024$, $p < .001$), and positively associated with seek ($\tau = 0.050$, $p < .001$) and backward navigation ($\tau = 0.016$, $p = .027$).

Finally, school type showed a positive correlation with ESC ($\tau = 0.122$, $p < .001$) and CTDI ($\tau = 0.135$, $p < .001$), suggesting that students from more advanced educational institutions (e.g., high school) were more likely to both identify credibility cues and source reliability, aligning their trust judgments with normative expectations. This finding supports the role of cognitive development and curricular exposure in fostering epistemic evaluation skills.

3.3 Predictive modeling of epistemic trust judgments (RQ3)

Predictive modeling of epistemic trust judgments. To evaluate our third research question regarding the predictive capacity of different variable combinations, we developed three logistic regression models: Model 1a (using only navigation traces), Model 1b (adding emotional positioning and disposition to critical thinking), and Model 2 (incorporating selected potential interaction effects identified in our correlation analysis). Figure 7 presents a comprehensive comparison of these models across multiple performance metrics.

Model Performance Analysis. The progression across the three models reveals a substantial improvement in predictive power when incorporating emotional positioning and critical thinking disposition dimensions. Model 1a, based solely on navigation behaviors, showed modest performance with an accuracy of 55.7% and an AUC-ROC of 59.5%. While this demonstrates that navigation traces alone contain some predictive information, the relatively low metrics suggest that behavioral data in isolation provides an incomplete picture of epistemic judgment processes. Model 1b, which incorporated emotional positioning and critical thinking disposition, demonstrated a marked improvement across all metrics, with accuracy increasing to 69.3% (+13.6 percentage points) and AUC-ROC reaching 74.0% (+14.5 percentage points).

Table 6. Partial correlations between navigation behaviors, attitude, and critical thinking disposition measures (Kendall's Tau).

A

		CTDI	play	paused	stoped	seek	forward	back
CTDI	Kendall Tau B	—						
	p-value	—						
play	Kendall Tau B	0.005	—					
	p-value	0.542	—					
paused	Kendall Tau B	0.013	-0.687 ***	—				
	valeur p	0.086	< .001	—				
stoped	Kendall Tau B	-0.009	-0.358 ***	-0.172 ***	—			
	p-value	0.223	< .001	< .001	—			
seek	Kendall Tau B	-0.019 **	-0.364 ***	-0.163 ***	-0.084 ***	—		
	valeur p	0.010	< .001	< .001	< .001	—		
forward	Kendall Tau B	0.005	-0.316 ***	0.264 ***	-0.035 ***	0.190 ***	—	
	p-value	0.509	< .001	< .001	< .001	< .001	—	
back	Kendall Tau B	0.013	-0.000	-0.036 ***	-0.048 ***	0.105 ***	-0.136 ***	—
	p-value	0.078	0.982	< .001	< .001	< .001	< .001	—

Note. controling for 'video_id' et 'School_type'
Note. * p < .05, ** p < .01, *** p < .001

B

		CTDI	play	paused	stoped	seek	forward	backward	ESC	bin_Att	School_type
CTDI	Kendall Tau B	—									
	p-value	—									
play	Kendall Tau B	0.008	—								
	p-value	0.297	—								
paused	Kendall Tau B	0.004	-0.687 ***	—							
	p-value	0.549	< .001	—							
stoped	Kendall Tau B	-0.014	-0.358 ***	-0.169 ***	—						
	p-value	0.064	< .001	< .001	—						
seek	Kendall Tau B	-0.007	-0.361 ***	-0.167 ***	-0.087 ***	—					
	p-value	0.330	< .001	< .001	< .001	—					
forward	Kendall Tau B	0.006	-0.315 ***	0.262 ***	-0.035 ***	0.190 ***	—				
	p-value	0.389	< .001	< .001	< .001	< .001	—				
backward	Kendall Tau B	0.014	0.000	-0.036 ***	-0.049 ***	0.106 ***	-0.136 ***	—			
	p-value	0.052	0.991	< .001	< .001	< .001	< .001	—			
ESC	Kendall Tau B	0.280 ***	0.024 **	0.018 *	-0.019 **	-0.053 ***	0.001	-0.001	—		
	p-value	< .001	0.001	0.015	0.010	< .001	0.936	0.890	—		
bin_Att	Kendall Tau B	-0.024 **	-0.021 **	-0.013	0.009	0.050 ***	-0.003	0.016 *	-0.007	—	
	p-value	0.001	0.005	0.071	0.245	< .001	0.714	0.027	0.329	—	
School_type	Kendall Tau B	0.135 ***	0.024 **	-0.061 ***	-0.035 ***	0.087 ***	0.011	0.011	0.122 ***	0.139 ***	—
	p-value	< .001	0.001	< .001	< .001	< .001	0.123	0.155	< .001	< .001	—

Note. controling for 'video_id'
Note. * p < .05, ** p < .01, *** p < .001

This substantial enhancement underscores the crucial role of attitude and critical thinking disposition dimensions in the formation of epistemic judgments. Model 2, which included selected interaction terms based on our correlation analysis, showed slightly different performance characteristics compared to Model 1b. While accuracy (68.6%) and recall (68.8%) were marginally lower, specificity improved to 67.6% (+3.7 percentage points) and precision increased to 89.9%. Notably, Model 2 achieved the best balance between sensitivity and specificity, suggesting a more nuanced classification approach. This model is nearly as effective at identifying positive cases as Model 1b (68.8% vs. 70.6%), but significantly better at identifying negative cases (67.6% vs. 63.9%). It does not excessively favor one class over the other.

Figure 7. Comparative metrics of logistic predictive models

1. Classification Performance Metrics

Metrics	Model1a	Model1b	Model2
Accuracy	55,7 %	69,3 %	68,6 %
Recall	55,3 %	70,6 %	68.8 %
Specificity	57,4 %	63,9 %	67,6 %
Precision	84, 5 %	89,2 %	89,9 %
F1 Score	66,9 %	78,8 %	78 %
AUC-ROC	59,5 %	74 %	74,8 %
Log-Loss	47,9 %	43,08 %	42,7 %

2. Model Characteristics

Characteristics	Model1a	Model1b	Model2
Number of variables	7	9	14
Significant variables	4 (+ int.)	5 (+int.)	7 (+int.)
AIC	7753.9	6981.3	6923.7
McFadden's pseudo-R^2	0.02	0.12	0.13
Deviance	7739.9	6963.3	6895.7

Note : int. = intercept

3. Cross-Validation metrics

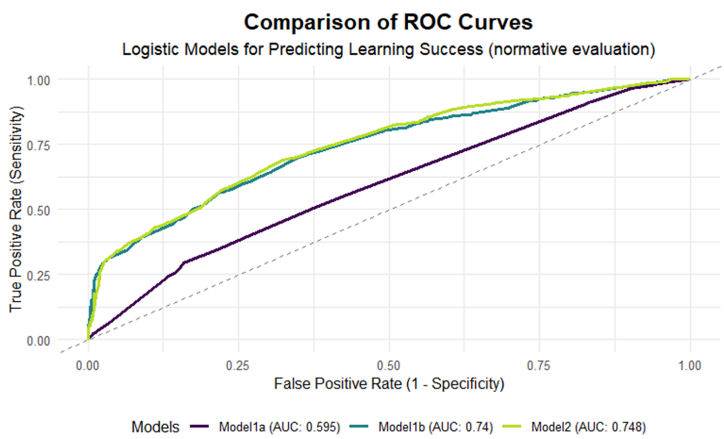
Metrics	Model1a	Model1b	Model2
Mean Accuracy (CV)	52,81 %	67,82 %	68,08 %
SD of Accuracy (CV)	4,56 %	2,82 %	1,88 %
Mean F1 Score (CV)	63,39 %	77,47 %	77,54 %
SD of F1 Score (CV)	5,55 %	2,53 %	1,69 %

Note : CV = 10-fold cross-validation

4. Robustness Analysis:

	Model1a	Model1b	Model2
1	☆☆	☆☆☆	☆☆☆☆
2	☆	☆☆☆	☆☆☆☆
3	☆	☆☆☆	☆☆☆☆☆

1 :Overfitting (Resistance) ; 2 :Imbalanced Data (Performance)
3 : Prediction Stability



Model Characteristics and explanatory power. The model complexity progressively increased from 7 variables in Model 1a to 14 in Model 2, with the number of significant predictors rising from 4 to 7. Both the Akaike Information Criterion (AIC) and deviance values showed substantial improvement from Model 1a to Model 2 (AIC: 7753.9 to 6923.7; Deviance: 7739.9 to 6895.7), indicating better model fit despite the increased complexity. McFadden's R^2 increased from 0.02 to 0.13, demonstrating improved explanatory power. Cross-validation results further confirmed the superiority of Models 1b and 2 over Model 1a. The mean cross-validated accuracy increased from 52.81% (Model 1a) to 68.08% (Model 2), with a concurrent reduction in standard deviation from 4.56% to 1.88%, indicating enhanced stability. Similar improvements were observed for the F1 score, with Model 2 showing the highest mean (77.54%) and lowest variability (SD = 1.69%).

Model Robustness Evaluation. We evaluated model robustness across three key dimensions: resistance to overfitting, performance on imbalanced data, and prediction stability. Model 2 demonstrated superior performance across all three criteria, with minimal overfitting (0.52% gap between training and cross-validation accuracy), strong performance on imbalanced data (AUC-ROC of 74.8% with well-balanced sensitivity and specificity), and excellent prediction stability (lowest standard deviations in cross-validation metrics). Model 1b showed good performance across these dimensions but was slightly less stable than Model 2. These results strongly support our third hypothesis.

4. Findings

Our study shows that such constructs can help explain how students process information and attribute trust—particularly in controversial video-based contexts, where credibility and expertise must be actively assessed. Specifically, 2 findings emerged from this study.

Regarding the first research question, which explored the extent to which students' navigation behaviors (e.g., pausing, seeking) are associated with their attitudes toward video content and their disposition to critical thinking, our findings reveal a nuanced relationship. **Our analysis suggest that learners' immediate perceptions and judgments of content may play a more prominent role in shaping how they interact with educational videos than more stable, underlying dispositions (Finding 1)**. Specifically, while critical thinking disposition appears to be only weakly reflected in navigation behaviors, students' attitudes toward the video content significantly influenced their engagement patterns. This was evidenced by distinct interaction behaviors—such as pausing and seeking—being more closely aligned with students' attitudinal responses than with their dispositional traits (Finding 1, related to RQ1).

Regarding Research Question 2, which examined how attitude, disposition to critical thinking, navigation behaviors, and institutional context influence the quality of students' trust judgments—defined as the degree to which their reported trust aligns with academic expectations—our analysis reveals a complex interplay among these factors. We found that **normative trust judgments are shaped by an interaction of dispositional, attitudinal, behavioral, and cognitive factors (Finding 2)**. The analysis shows that students from different institutional contexts (e.g., middle school vs. high school) exhibited varying levels of normative trust judgment, suggesting that school level may influence evaluative performance, possibly due to developmental differences or curricular exposure.

Moreover, critical thinking disposition was a strong predictor of normative trust alignment, particularly when combined with active navigation behaviors such as pausing and seeking. These patterns suggest that attitudinal alignment influenced normative evaluation by **affecting** how learners engaged with the content and how critically they processed it. As previously noted, attitudinal agreement may dampen epistemic vigilance by reducing the need for critical scrutiny when encountering familiar or confirming content.

Regarding the third research question—whether a model that integrates students' video interaction behaviors, critical thinking disposition, and attitudinal alignment better predicts performance on an academic evaluation task than one based solely on navigation data—the findings provide strong empirical support for the extended model. While the baseline model (Model 1a), based only on navigation behaviors, showed modest predictive power, the inclusion of affective and cognitive dimensions in Model 1b substantially improved accuracy and discriminative ability. Model 2, which further incorporated interaction terms informed by correlation analyses, offered the best overall balance between sensitivity and specificity. Importantly, Model 2 was also the most robust, demonstrating minimal overfitting, superior handling of imbalanced data, and high prediction stability across cross-validation folds. This balance is particularly important in educational contexts where both false positives (e.g. incorrectly identifying a student as mastering a concept) and false negatives (e.g. failing to recognize that a student has mastered a concept) have significant pedagogical implications. These results highlight the added value of integrating dispositional and attitudinal variables when modeling epistemic evaluation behaviors. They also reinforce the idea that learning analytics models benefit significantly from a multidimensional approach that accounts not just for what learners do, but how they feel and think as they engage with content. This has important implications for the design of predictive systems in education, where both accuracy and fairness in identifying learners' needs are critical for effective support.

5. Conclusions and Future Directions

This study shows that trust attribution in educational videos is shaped not only by students' interaction behaviors, but also by their critical thinking disposition and attitude toward the content. Incorporating attitude and critical thinking disposition significantly enhances the predictive understanding of epistemic judgments in video-based learning environments.

The findings presented in this paper contribute to a growing body of research highlighting the importance of integrating cognitive, affective, and dispositional dimensions into the analysis of digital learning. While navigation traces have traditionally been interpreted through a technical lens, our results support the idea that such behaviors can serve as markers of cognitive engagement and epistemic effort, particularly when analyzed in conjunction with students' attitudes and critical dispositions. These results are consistent with prior work emphasizing the role of dispositions in digital learning behavior analysis [25]. Indirectly, our findings also reinforce previous insights into the role of emotions as epistemic cues [12, 23], particularly in video-based contexts where multisensory presentation can trigger affective heuristics [19]. The observed negative association between attitudinal alignment and normative success during evaluation task suggests that prior agreement with content may reduce epistemic vigilance, as learners feel less compelled to interrogate information that aligns with their beliefs. From a methodological perspective, our results support the value of integrating psychological constructs such as attitude and disposition to critical thinking into predictive models.

Pedagogically, these findings suggest that fostering critical reflexivity in learners requires more than teaching analytical skills: it also involves raising awareness of one's emotional and attitudinal positioning when faced with persuasive content. Designing learning environments that explicitly address epistemic strategies—for example by encouraging disagreement, justifications, or source comparisons—could support students in developing more robust habits of critical engagement, particularly in a media landscape saturated with affective and ideological content. In this regard, the Critical Thinking Disposition Indicator (CTDI) offers a valuable analytical lens for identifying students' underlying skills.

Future research should explore more sophisticated modeling approaches (RandomForest, XGBoost, GRU neural network) that include contextual and psychological moderators, and investigate how these variables evolve over time. One additional consideration might be to explore how different demographic and educational background factors moderate these relationships. This could help create more personalized approaches to supporting critical thinking in diverse student populations. Experimental studies targeting video characteristics could further elucidate the causal mechanisms at play. Translating these findings into educational interventions to support critical engagement with online video content remains a key practical goal.

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