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Investigating the Effectiveness of Explanations in Active Video Watching

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Abstract: The use of video-based learning (VBL) has increased in recent years due to its effectiveness in distance learning. However, challenges in VBL, such as passive learning and low levels of engagement, continue to exist. Active Video Watching (AVW) addresses these challenges by supporting students' engagement and learning via features such as personalized nudges and visualizations. Furthermore, the AVW platform used in our research utilizes an AI model to classify comments students write on videos into several comment quality categories. Explanations of how comments are classified may enable students to understand the comment quality and, subsequently, write better comments. To determine whether explanations of comment quality would benefit students, we conducted a quasi-experimental study wherein we compared data collected from software engineering students at the Ateneo de Davao University (control group, 55 students using the AVW platform without explanations) to data collected from a comparable course at the University of Canterbury (experimental group, 45 students who received explanations). This study included a survey on students' perceptions on explanations. Results show that students in the experimental group, especially those who accessed explanations for multiple comments, wrote more higher-quality comments. Results of the survey show students are satisfied with explanations, particularly regarding the clarity, correctness, and the level of detail of explanations. This research contributes to using explanations in VBL platforms to increase learning and engagement.

Keywords: Video-Based Learning, Active Video Watching, Explanations, Explainable Artificial Intelligence

1. Introduction

Videos have become a popular and widely used method of learning (Fyfield et al., 2019). Video-based learning (VBL) is flexible, easy to use, provides opportunities for self-regulated learning, improves student attention, and increases motivation and engagement (Chatti et al., 2016, Dimitrova and Mitrovic, 2022, Seo et al., 2021). Furthermore, supplementing VBL with Artificial Intelligence (AI) can present more opportunities for engagement and learning (Seo et al., 2020). For example, Mohammadhassan et al. (2020) used a machine learning module to classify the quality of comments students write on videos and provide adaptive nudges to students, encouraging them to write better comments.

As with many VBL platforms, despite the perceived benefits of AI, the decision-making processes and the reasoning behind these AI predictions made are not visible to learners (Porayska-Pomsta et al., 2023, Edwards and Veale, 2017). These concerns have paved the way for explanations in AI in Education (AIED) systems and the adoption of explainable artificial intelligence (XAI) techniques (Farrow, 2023). Different studies have been conducted related to explanations and XAI in Education (XAI-Ed) (Türkmen, 2024), but explanations in AI-supported VBL have been scarce. With VBL being a popular method for teaching (Sablić et al., 2021), effective implementation of VBL, especially when AI is integrated, is vital (Seo et al., 2020). Explanations is a way to strengthen the use of VBL in learning. Moreover, it is also important to evaluate explanations (Markus et al., 2021) and identify if these fit the needs of learners (Adadi and Berrada, 2018). This highlights the importance of exploring explanations of AI features in VBL.

This research investigates the effectiveness of integrating explanations of the AI-supported automatic assessment of comment quality in a platform for Active Video Watching (AVW). AVW-Space, the AVW platform we used for this experiment, automatically assesses the quality of comments students write. In previous studies with AVW-Space, the feedback from students included the need for explanations of the AI-generated comment quality. In this study, we added explanations and investigated their effects explanations on learning, engagement, and satisfaction. We aim to provide additional insights into the effects of explanations in VBL and contribute to the ongoing studies related to explanations in the area of AIED. We address the following research questions:

RQ1. Do explanations increase engagement and foster constructive behavior of learners? When explanations are available, we expect that students will engage with them, by accessing explanations of the quality of their comments, and also engage more with the platform (Hypothesis H1). Furthermore, while engaging with explanations, students would learn about how to write high-quality comments. With this, we expect more constructive learners in the experimental group (Hypothesis H2).

RQ2. Do explanations in AVW contribute to student learning? We anticipate that explanations of comment quality will have a positive effect on students' learning (Hypothesis H3). As mentioned, it is expected that explanations would clarify the reasons for comment quality and will prompt students to make more reflective or regulating comments.

RQ3. Are students satisfied with explanations in AVW? We will look into student feedback on explanations and identify if students have a positive perception of explanations to answer RQ3.

2. Related Work

2.1 Automatic Assessment of Comment Quality in AVW-Space

One effective form of video-based learning is Active Video Watching. AVW supports engagement in video-based learning by supporting self-regulated and reflective learning through a controlled video-watching environment (Mitrovic et al., 2016). AVW is scalable and provides a wide range of features to provide engagement when watching videos (Dimitrova and Mitrovic, 2022). AVW-Space is an AVW platform primarily used for soft-skills training (Mitrovic et al., 2019, Mitrovic et al., 2017). The platform allows teachers to create a space and integrate videos sourced from YouTube (Mitrovic et al., 2016). Using the space created by their teacher, students can watch videos and write comments.

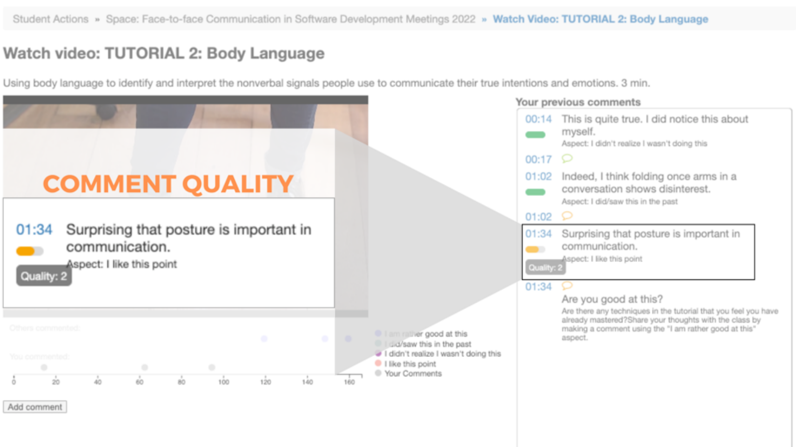

Figure 1. Comment quality feature in AVW-Space

The platform supports nudges (or personalized reminders) (Mitrovic et al., 2019), and includes automatic assessment of comment quality. This also is used for quality nudges (personalized reminders related to the quality of students' comments) (Mohammadhassan et al., 2022). Figure 1 shows a comment quality indicator, which is added to each comment to motivate students to write better comments (Mohammadhassan et al., 2020).

Mohammadhassan et al. (2020) proposed a quality scheme for comments on videos, with category one being of the lowest quality and category five as the highest. This labeling scheme is used in developing machine learning (ML) models to automatically assess the quality of students' comments (see Table 1). Comments in the first two categories are pedagogically undesirable and are considered low-quality comments as they do not convey deep thinking and reflection on the video content. The last three categories are considered high-quality, which convey critical thinking (category 3), reflection on past experiences or behaviors (category 4), or self-improvement (category 5) (Mohammadhassan et al., 2020).

Table 1. *Comment categories from Mohammadhassan et al. (Mohammadhassan et al., 2020)*

	Category	**Definition**
1	Affirmative, negative, off-topic	Comments which are irrelevant or merely affirmative/negative with no explanation
2	Repeating	Comments which only repeat the video content
3	Critical and analytical	Comments which mention points that are implicitly covered in the video or show critical thinking on the content of the video.
4	Reflective	Comments in which the learner reflects on their behaviour and previous experience or knowledge on giving presentations.
5	Regulating	Comments where the learner decides what they would do to improve themselves in future.

Machine learning is used to categorize user comments into quality categories. Currently, random forest is used for the assessment of comment quality as it was proposed by Mohammadhassan et al. (2020) as the best method among different classifiers when classifying comments from early studies in the same platform. Comments from previous experiments in AVW-Space were used to train and test the model. Predictions about the quality of comments from the model are used to generate quality nudges. Explaining this prediction can help students understand what good-quality comments are and help them formulate better comments.

2.2 Explanations in AIED and VBL

There have been several efforts to integrate explanations into AIED systems (Fiok et al., 2022). As AIED systems support different approaches to learning, explanations are personalized to the features of these systems (Zapata-Rivera and Arslan, 2024). Khosravi et al. (2022) presented a framework for XAI-ED, determined the application of XAI in different educational systems, and investigated four AIED systems integrating XAI. An example is RiPPLE by Darvishi et al. (2020), which uses explainable automated feedback on poor peer reviews that is supported by NLP models. Case studies like this aid the development of explanations in AIED systems, although there is need to explore further personalizing explanations (Khosravi et al., 2022). Personalizing explanation features, especially in educational systems, is highly recommended in literature (Conati et al., 2021, Kouki et al., 2019).

There is limited research on XAI in video-based learning. Although other XAI-ED frameworks or methods can be applied to AI-supported VBL systems, it is important to consider the personalization of explanations in VBL. Chen et al. (2023) proposed a similar recommendation to consider XAI in VBL to enhance social transparency and to develop a framework and expanded XAI framework for educational systems.

3. Explanations of Comment Quality in AVW-Space

We previously surveyed undergraduate students in order to identify the explanation requirements and the basis for the design, presentation, and timing of explanations in AVW (Lumapas et al., 2024). The findings showed that (1) students were primarily interested in explanations on how the comment quality is determined, (2) wanted to see explanations shown next to comments and (3) wanted explanations to be shown on-demand.

To generate explanations of comment quality, we use the comment text, its quality category, linguistic/textual features (e.g. nouns, pronouns, verbs, positive/negative words), and the selected *aspect* (teacher-defined micro-scaffolds for directing students to reflect on key points of the video or their experience (Mitrovic et al., 2017)). This information is then passed to a textual analysis feature, which checks for any contractions (e.g., "*I'm*", "*Don't*") or negative words or phrases (i.e., "*do not*", "*cannot*"). This process is necessary to identify if the comment is positive or negative, as the explanations are also determined based on the sentiment. The text of the explanation is determined by the quality, the textual features, and the general sentiment (positive/negative) of the comment. For high-quality comments, as there is no need for further support, a simple explanation is added (e.g., "This comment is a quality 4 (high-quality) comment because you made a personal reflection related to empathy").

Explanations of low/medium quality comments (quality 1 or 2) provide more information. These explanations consist of three parts: (1) an explanation of the comment quality, (2) a recommendation on how to improve the comment, and (3) an example of a better-quality comment, as illustrated in Figure 2. In most cases, category 1 or 2 comments are short; generally, they simply agree/disagree (e.g., *"Good"*, *"I agree"*), are off-topic, vague, repeating video text or content, or repeat the aspect text. Depending on the issues identified regarding the comment, we add an appropriate explanation. For example, if a comment just simply agrees *"This is correct"*, we add this to the explanation text: *"This comment is a quality 1 (low-quality) comment because you made a short affirmative/negative or off-topic comment."* The recommendation in this case is *"You can make this comment better by relating it to your or your team's experience"*. The explanation also contains an example of a higher-quality comment, such as *"Our team takes input from everyone when assigning tasks and knowing if they are capable or comfortable."*

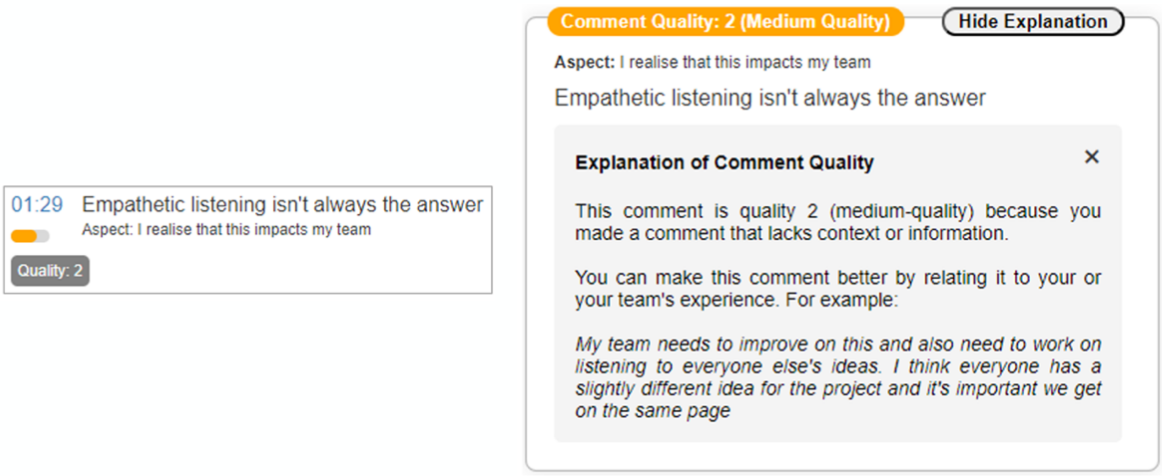

Figure 2. Comments without explanations (left) and comments with explanation (right)

Figure 2 shows the differences between comments without explanations and comments with explanations. This example shows a comment with a low quality with the commenter not relating to the aspect selected. The explanation shows comment quality by color (red for quality 1, yellow for quality 2, and green for high quality) and also text. Students can access and hide explanations.

4. Experiment Design

We conducted a quasi-experimental study with two groups of students at the Ateneo de Davao University (ADDU) in the Philippines, and at the University of Canterbury (UC) in New Zealand in 2024 (*Human Research Ethics Approval 2023/96/LR-PS and 2024/79/LR-PS*). Although students were from two different countries, they were enrolled in similar software engineering courses. Furthermore, although there are cultural differences between the two groups, both universities used English as the language of instruction. In both courses, students worked on a project in groups. Students who completed all training tasks were given 5% of the final course grade.

Explanations were introduced in AVW-Space used by UC students (experimental group) while the ADDU students did not have explanations (control group). Both groups used the platform for four weeks, and the learning materials and process were identical. The platform offered six five-to-ten-minute videos related to empathy in the context of software engineering. Students provided informed consent or opted out of participating in the study. In the latter case, students could complete the soft skills training and get course credit, but we did not collect data about them.

Two surveys were administered within AVW-Space, both of which contained a timed question (one minute) where students were asked to list all concepts they know about empathy. Responses were marked automatically using the ontology developed for empathy skills by the research team. The resulting Conceptual Knowledge score from Survey 1 (CK1) is the pre-test score, while CK2 from Survey 2 is the post-test score.

Survey 1 contained demographic questions. Survey 2 included seven questions about the explanation feature. Among these is an explanation satisfaction instrument derived from Hoffman et al.'s (2023) measures for XAI. There are seven statements in this instrument, and we used a Likert scale to identify if students agree/disagree with the statement (1 - Strongly Disagree to 5 - Strongly Agree). Another question asked students to select the reasons for seeking explanations. We also added open-ended questions on explanations, the purpose of re-reading/re-accessing explanations, and questions on their experience and suggestions. The platform also logged data about all actions students performed, such as log-ins, comments written and access to explanations.

We used the ICAP framework (Chi and Wylie, 2014), which classifies students based on their overt behaviors into Interactive, Constructive, Active, and Passive categories. Passive learners only watched the videos without writing comments. Active students wrote comments of low quality; they repeated the information provided in the videos without any reflection or elaboration. Constructive students reflected on the videos and added new information not explicitly taught. We do not consider the interactive category from ICAP (which promotes interaction between students), as interaction was not supported by the platform.

5. Results

We analyzed the data about the students who completed both surveys and watched at least one video (Table 2). There are 54 students in the control and 44 in the experimental group.

Table 2. *Number of responses to survey and completion of soft-skills training.*

Group	Survey 1	Watched Videos	Survey 2
Control	78 (69.6%)	**54 (48.2%)**	56 (50.0%)
Experimental	50 (94.3%)	49 (92.5%)	**44 (83.0%)**

5.1 Effects of Explanations on Engagement (RQ1)

Table 3 shows how students interacted with the platform. The experimental group accessed the platform more often than the control group, measured both by the number of days the platform was used and the number of sessions, which confirms our hypothesis H1. There are no significant differences between the groups in the number of nudges, comments made, and the number of videos watched and commented on. However, there is a significant difference in the number of high-quality comments.

Table 3. *Engagement mean (STDEV)*

	Control (54)	**Experimental (44)**	**t-test**
Days on the Platform	4.22 (1.819)	8.44 (3.057)	t=8.507, p<.001
Sessions	4.78 (2.229)	9.89 (4.350)	t=7.534, p<.001
Nudges	26.94 (11.758)	27.82 (7.243)	t=.436, p=.332
Videos	5.91 (0.680)	6.00 (0.00)	t=.912, p=.182
Comments	10.72 (7.720)	10.87 (4.971)	t=.108, p=.457
Videos Commented	5.83 (0.855)	6.00 (0.00)	t=1.294, p=.099
High-Quality Comments	5.78 (5.62)	10.36 (4.75)	t=4.323, p<.001

We categorized the students post-hoc into the ICAP categories. We classified students who watched without making any comments as *"Passive"*. Consistent with findings from the previous studies with AVW-Space, interventions introduced to support student learning reduce the number of passive students (Mohammadhassan et al., 2020; 2022; Mitrovic et al., 2019). This is observed in our study too, as there were no passive students in either group. Meanwhile, to differentiate between the *"Constructive"* and *"Active"* students, we used the median number of high-quality comments made on the videos (Mohammadhassan et al., 2022). The median number of high-quality comments was seven, which means that those who commented eight or more high-quality comments were classified as *"Constructive"*. Those who wrote up to seven high-quality comments are considered as *"Active"*.

We performed a Chi-square test of homogeneity between the two groups and the ICAP categories. Results show a significant difference (Chi-square = 10.433, p=.001) with effect size (Phi) of .325 (p=.001). In the post-hoc analysis, we observed that there was an increase in the number of Constructive students in the experimental group in comparison to the control group (Table 4). The higher number of participants from the experimental group who are constructive learners confirms Hypothesis H2.

Table 4. *Numbers of constructive and active students in the two groups*

	Control (54)	**Experimental (44)**	**t-test**
Active	39 (86.7%)	18 (40.0%)	p<0.001
Constructive	15 (33.3%)	27 (60.0%)	p<0.001

We also investigated the access to explanations between the different ICAP categories in the experimental group. Table 5 shows that constructive students accessed more explanations in comparison to active students. Similarly, the number of unique comments for which the explanation was accessed is higher for constructive students than active students.

Table 5. *Comparing active and constructive students from the experimental group*

	Active (18)	**Constructive (27)**	**t-test**
Times Explanations is Accessed	1.72 (1.02)	4.63 (3.38)	t=3.536, p=.001
Unique Comments where Explanations was accessed	1.61 (0.85)	3.74 (2.40)	t=3.612, p=.001

5.2 Effects of Explanations on Learning (RQ2)

We first analysed whether the two groups are comparable in terms of their pre-existing knowledge of empathy. The Kolmogorov-Smirnov test confirmed that the CK1 scores were not distributed normally (p < .05). The comparison of CK1 scores for the two groups using the Mann-Whitney U-Test shows that the distribution of the CK1 scores is the same across the two groups of students (U = 1397.5, p = .198). Table 6 details the differences in the CK1 and

CK2 scores in the two groups, showing the mean scores and the standard deviation. In the control group, there is little difference between the CK1 and CK2. There is a higher CK2 score as compared to the CK1 score for the experimental group.

Table 6. *Conceptual Knowledge Scores - Mean and Standard Deviation*

Group	CK1	CK2
Control	9.13 (8.74)	9.20 (8.78)
Experimental	7.82 (7.82)	11.27 (6.81)

We also analyzed the number of comments, especially high-quality ones, as a potential indicator of learning. As mentioned earlier, most students who accessed explanations were constructive. Table 7 shows the average number of comments for each comment category (with categories 3-5 shown together as High-quality) by group. We observed that the experimental group had a higher average of high-quality comments than the control group ($t=4.323$, $p<0.001$). Comments from the control group, on the other hand, are divided between category two and high quality. There were also several category 1 comments in the control group, while the experimental group did not have any. Students from the experimental group consistently have high-quality comments, with 95.7% of the comments being quality 3-5. The control group, on the other hand, only 53.9% of the comments are high-quality.

Table 7. *Mean and Standard Deviation based on the comment categories for both groups*

Group	Category 1	Category 2	High Quality
Control	0.07 (0.26)	4.87 (4.93)	5.78 (5.62)
Experimental	0 (0.00)	0.47 (0.97)	10.36 (4.75)

As presented in Table 4, there are more constructive students in the experimental group than in the control group. We analysed whether there are differences as to the number of comments between the different ICAP groups in both groups (Table 8). The constructive students in both groups have the same average number of high-quality comments (13.07 and 13.00, respectively). This would mean that explanations of comment quality enable students to write comments that are critical, reflective, and regulating.

Table 8. *Comment Quality per ICAP categories Mean and Standard Deviation*

Group		Category 1	Category 2	High Quality
Control	Active	0.10 (0.31)	4.56 (4.91)	2.97 (2.22)
	Constructive	0.00 (0.00)	5.67 (5.05)	13.07 (5.24)
Experimental	Active	0.00 (0.00)	0.22 (0.73)	6.39 (0.61)
	Constructive	0.00 (0.00)	0.630 (1.079)	13.00 (4.455)

There are significantly more high-quality comments in the experimental group compared to the control group. Most students in the experimental group were constructive students, who and wrote critical, reflective, or regulating comments. As presented in Table 8, even active students in the experimental group wrote mostly high-quality comments. Furthermore, we can observe that in the experimental group, the mean for low-medium quality comments is very low (0 for category 1 and 0.22 and 0.630 for active and constructive students respectively). This confirms Hypothesis H3.

5.3 Explanation Satisfaction (RQ3)

Results of Survey 2 conducted with the experimental group show positive perceptions of explanations. Table 9 shows that most participants agreed that the explanations were presented clearly (mean=4.05), are correct (mean=3.89), and provide sufficient detail (mean=3.89). Participants also noted that the explanations are predictable (mean=3.83). Predictability is not necessarily negative (Chamola et al., 2023, Zhou et al., 202). Finding the explanations as predictable can mean that the participants understood the content of the explanations well. We also looked into responses on whether explanations motivated students to write better comments. For that specific question, the mean score is 3.59. Students had varying opinions, which is reflected in the standard deviation value of 1.11, the highest in the explanation satisfaction questions. Most students, however, answered *“somewhat agree”* (25%) or *“strongly agree”* (27%) to the question on motivation.

Table 9. *Explanation Satisfaction Results*

Question	**Mean (SD)**
I understand how comment quality is determined based on the explanations	3.68 (1.02)
Explanations have sufficient detail	3.89 (0.80)
Explanations are predictable	3.82 (0.91)
Explanations are correct	3.89 (0.86)
Explanations are presented clearly	4.05 (0.74)
Explanations motivate me to write better comments	3.59 (1.11)
Explanations are useful	3.64 (0.86)

We examined the responses to the open-ended question, "How would you describe your experience with explanations?" Thirty-one (31) out of 44 participants (70%) had a positive perception towards explanations. Most students who accessed explanations found them beneficial. Explanations helped students to reflect on the task and comments made (e.g., *"Overall it was a positive experience. It helped give a brief period of reflection on each comment. It was nice to ‘quantify’ the quality of each comment, even if it wasn't fully clear as to why a rating was given"*). Some comments indicate self-regulation, where students mention that explanations help them improve their future comments (e.g., *“It was good! When my comment was of lower quality, I would always check the explanation and read the reason so I could improve my comments next time. One in particular that I remember is when I was commenting, often I would just write about how I agreed with what was being said, but the explanations helped to realize that a better comment would be self-reflective on my own experience”*). Other than improving on the tasks associated with the training, some students do mention the benefits of explanations in improving their understanding of the concepts mentioned in the videos (e.g., *"Helpful as I was able to gain a deeper understanding of what we are learning and how I can apply this to my personal participation in teamwork and in <Course Code>."*).

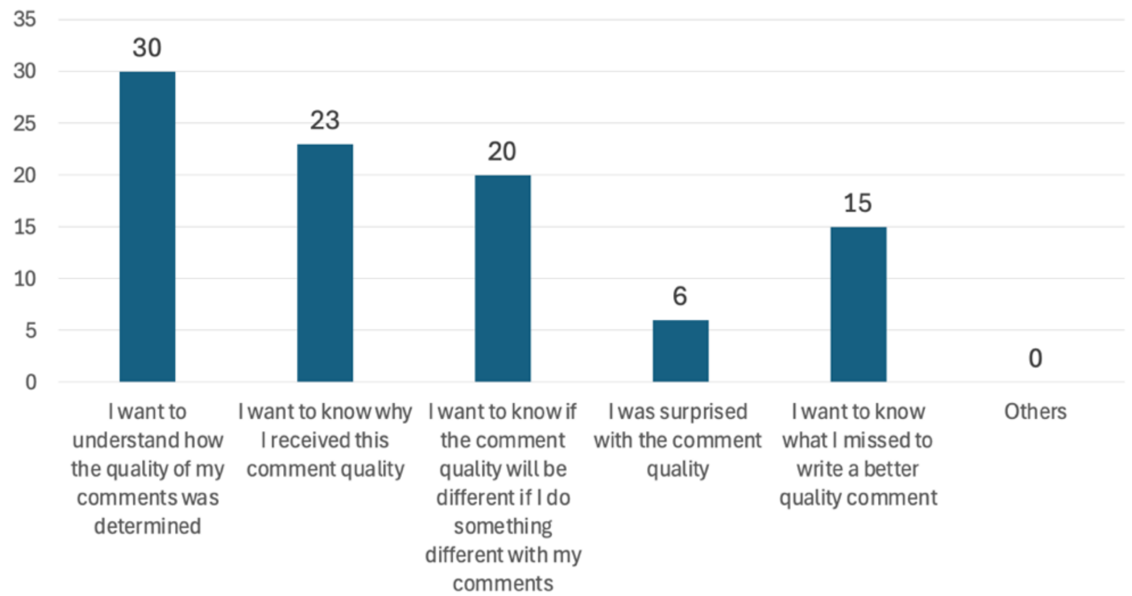

Figure 3. Reasons for seeking explanations

Interestingly, one participant mentioned the straightforward nature of the explanations is a reason to not access explanations for other comments anymore, mentioning, *"I think I quickly grasp onto explanation and don't need too much to rethink about it too much or have to go back to re-read an explanation".* This might mean that students might have understood the explanation when they saw it the first time and did not need to re-read explanations.

We also asked students in Survey 2 to select the reasons why they asked for explanations (Figure 3). Students could select multiple responses and could also select "Other" to specify a reason that was not listed. 29 out of the 44 students (65.9%) in the experimental group added more than one reason. Meanwhile, no students indicated their own reasons outside of the selection. Students mostly accessed explanations to understand how the comment quality was determined. However, some students also indicated that they accessed explanations to improve their comments.

6. Discussion and Conclusions

We proposed adding explanations of the quality of comments written for videos in VBL, in order to support learning and increase engagement. We found that explanations fostered constructive behavior, reflected in an increase in the number of students in the experimental group. We also identified that students who accessed explanations spent more time (i.e., days and sessions) on the platform and wrote more high-quality comments. It was observed that explanations affect engagement and are helpful for learners. Although we did see an increase in the number of high-quality comments in the experimental group, we plan to conduct more studies to further identify whether there is a direct effect of explanations on learning.

One limitation of our study is the small size of the experimental group, which is not sufficient to identify causation of explanations on learning. However, we can conclude that explanations can aid students in writing reflective and regulating (high-quality) comments and support constructive learning. Furthermore, students recognized the positive impact of explanations. Explanations promote reflection when commenting on the videos and help students improve their comments. To identify a potential causal relationship between our intervention and learning gain, more participants are needed. It is important to note that the current participants identified that explanations were presented clearly and had sufficient detail. Although, an analysis of the CK1 scores indicated that there is no significant difference in prior knowledge between the two groups, it is noted that differences in cultural and educational backgrounds may contribute to differences in the CK2 scores. Another method of measuring increase in learning should be used in future experiments.

As discussed earlier, the literature on explanations in VBL is limited. Our research contributes to exploring explanations as a way to support and boost learning and engagement in VBL. This research contributes to the expanding pool of research looking at explainability in learning systems, given the importance of explanations in promoting trust and transparency in a time when AI is more utilized in education.

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