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Using Video Activity Reports to Support Remote Project-Based Learning

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Abstract: Distance learning has been expanding. Learner engagement is particularly important in project-based learning (PBL), but the interaction between teacher and learner and the understanding of learner status, including engagement, is not easy. This study aims to support teacher-learner communication based on learner engagement for remote PBL. In this paper, we propose the use of video activity reports by learners to estimate and understand learner engagement and to demonstrate its feasibility on the basis of the relationship between verbal and nonverbal information that can be obtained from video activity reports and learner engagement. Analysis of 232 video activity reports submitted by eight graduate students while working on remote research-based PBLs reveals that learner engagement decreases (1) when the report contained negative words, (2) when filled pauses were frequent or long, and (3) when silent pauses were infrequent or short. Furthermore, the feasibility of an AI-based support system is demonstrated through the design and implementation of a prototype.

Keywords: Distance learning, Project-based learning, Engagement, Video activity report, Artificial intelligence
Categories: H.5.3, L.3.5, L.3.6
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1 Introduction

Remote work has grown in popularity in recent years. This involves working without space or time limits [Olson, 1983, Beckel and Fisher, 2022]. It can reduce stress, improve quality of life, and boost well-being [Bailey and Kurland, 2002, Gilson et al., 2015]. Remote work will likely remain popular in the future.

Work engagement is often a focus in the context of work. Work engagement indicates the positive mental state of workers toward their jobs [Kahn, 1990, Schaufeli et al., 2002b, Harter et al., 2002]. It has been shown that when work engagement declines, employees' belongingness to the company, task performance, and motivation are reduced [Harter et al., 2013, Schaufeli and Bakker, 2004]. Managers can help employees maintain their performance when work engagement declines. Therefore, measuring work engagement in remote work is a necessary aspect of managing employees.

Several challenges arise in remote work, including reduced communication opportunities [Mulki et al., 2009, Bezerra et al., 2020, Johnson et al., 2021]. This can affect relationships or task performance and cause mental health issues [De Vincenzi et al., 2022]. It has also been pointed out that lack of communication opportunities can lead to lower work engagement [Galanti et al., 2021].

To address the lack of communication opportunities in remote work, previous studies have focused on activity reports, which are exchanged between managers and employees to report daily operations [Pogorilich, 1992, Lu et al., 2018]. Video activity reports contain verbal and nonverbal information and provide more information than text-based reports. He et al. showed the relationship between video activity reports and engagement, demonstrating the usefulness of video activity reports for remote work [He et al., 2022].

Distance learning is also a form of remote work, as it is a remote activity that is not restricted by time or space. In distance learning, students can learn from home without attending school [Chen et al., 2021] and watch on-demand class videos whenever they wish [Cojocariu et al., 2014, Adnan and Anwar, 2020]. Distance learning has also been criticized as a possible cause of a decline in learner engagement due to reduced communication opportunities [Longhurst et al., 2020, Wilcha et al., 2020, Lee et al., 2020]. Communication support in distance learning is necessary because reduced engagement can lead to negative effects, such as reduced task performance [Tanaka et al., 2021, Zhuang and Chen, 2020].

This study aims to support communication between teachers and learners in distance learning. For our purpose, we propose using video activity reports to help teachers estimate and understand learner engagement. It is expected that teachers will be able to increase communication opportunities between themselves and students whose engagement is declining by understanding learner engagement. Increased communication opportunities are also expected to lead to increased learner engagement. This study focuses on the learner engagement of students engaged in project-based learning (PBL).

PBL is a pedagogical approach that combines knowledge acquisition and problem solving [Markham, 2011]. To demonstrate the effectiveness of PBL in computer science, McManus and Costello conducted PBL to ask students to investigate the feasibility of an unmanned aerial vehicle (UAV) at low monetary cost and to implement it. As a result, students acquired not only specialized knowledge and skills but also time management and presentation skills [McManus and Costello, 2019]. In addition, Chounta et al. employed PBL in a camping-style setting, in which small teams worked on programming tasks. Every team that participated in this PBL received high assessments in terms of creativity and novelty, among other criteria [Chounta et al., 2017]. A common point in these examples of PBL is that learners progressed their learning activities on their own. PBL requires learners to not only complete tasks given by the teacher but also find their own tasks and perform their own learning activities with the support of teachers [Markham, 2011]. Therefore, learner engagement, which indicates a positive mental state toward a task, is essential for the success of PBL.

Similarly, in the present study, students determined a research theme, learned research methods, and proceeded with a research project while applying the methods. Although the teacher was a supervisor, they did not direct all of the students' tasks. Thus, the activity in this study can be regarded as PBL. This study focused on learner engagement over several months during the PBL period.

To understand the learner engagement of students engaged in distance PBL using video activity reports, it is necessary to clarify the relationship between video activity reports and learner engagement. In this study, we analyzed the relationship between 232 video activity reports of eight graduate students obtained by He et al. [He et al., 2022] and learner engagement on that day.

We also created a system prototype to help teachers. We discussed how the findings of this study can be utilized and what aspects should be the focus of the system.

The contributions of this study are as follows.

– Based on the verbal and nonverbal information in the video activity report, we revealed the following relationship regarding the engagement of students engaged in PBL activities:
  - Engagement declines when negative phrases appeared in video activity reports.
  - Engagement declines when the frequency of filled pauses is high or when the duration of filled pauses is long.
  - Engagement declines when the frequency of silent pauses is low or when the duration of silent pauses is short.
– Demonstrated a system prototype that allows teachers to grasp learner engagement using video activity report and showed prospects of the system using AI technology.

2 Related Work

2.1 Issues in Remote Work

Studies comparing work in face-to-face environments with remote work have been conducted in recent years. It has been reported that the diversity of home environments and life rhythms in teleworking must be considered to avoid failure in work coordination and communication [Breideband et al., 2022]. Other studies have claimed that remote activities between teams do not always work well, even if they work well within a team [Hu et al., 2022], and that office work and work-from-home work cannot be coordinated in the same way [de Souza Santos and Ralph, 2022]. These studies have pointed out that communication and coordination issues related to remote work.

One problem with remote work is the lack of communication opportunities [Mulki et al., 2009, Bezerra et al., 2020, Johnson et al., 2021]. Communication between teachers and students in remote environments may also be reduced, which impedes learning activities. When collaborating with multiple people, teamwork and collaboration can be inhibited in a remote environment [Sarker et al., 2012, Pyöriä, 2011, Baruch, 2000, Pearlson and Saunders, 2001]. It has also been suggested that poor communication may hinder team morale [Overmyer, 2011, Tremblay and Thomsin, 2012] or reduce team commitment [Golden, 2009].

These studies indicate that it is necessary to support communication in distance learning.

2.2 Engagement

One measure of mental state is engagement, which relates to motivation [Kahn, 1990, Schaufeli et al., 2002b, Harter et al., 2002]. Motivation is the willingness to perform a task, whereas engagement indicates positivity when immersed in a task [Afflerbach and Harrison, 2017]. High engagement indicates a positive mental state, leading to better task performance [Harter et al., 2013] and increased organizational belonging [Schaufeli and Bakker, 2004].

Many studies in the field of education have focused on engagement as a noncognitive factor that influences learning [McGill et al., 2019]. In the educational context, this has commonly been referred to as "student engagement" since the 1980s [Trowler, 2010]. Marks defined it as "the attention, interest, investment, and effort students expend in the work of learning" [Marks, 2000]. Learner engagement contributes to social and cognitive development and improves academic performance [Finn and Zimmer, 2012, Schaufeli et al., 2002a, Loscalzo and Giannini, 2019, Dimitriadou et al., 2020], while reduced engagement increases dropout risk [Schaufeli et al., 2002a, Rumberger, 1987]. These studies show that learner engagement is worthy of attention in the field of education.

There are different definitions of engagement in different fields, including education and psychology [Azevedo, 2015]. This study follows the definition by Schaufeli et al., who state that "engagement is characterized by vigor (high activation) and dedication (high identification). Furthermore, ..., and engagement includes absorption" [Schaufeli et al., 2002b]. This definition is often used in computer-supported cooperative work. They proposed that engagement is the opposite of burnout. Vigor (high activation) and dedication (high identification), which are the components of engagement, are the opposite of exhaustion (low activation) and cynicism (low identification), which are two of the three components of burnout. Absorption, the third component of engagement, which was added based on the interview survey results, corresponds to reduced efficacy, the third component of burnout [Schaufeli et al., 2002b].

Engagement is affected by job resources (e.g., autonomy, feedback, and social support), personal resources (e.g., optimism, self-efficacy, and resilience), and job demands (e.g., work pressure and physical/mental demands). Demerouti et al. proposed the JD-R model, which suggests that an imbalance between the two resources and demands can cause burnout [Demerouti et al., 2001]. Bakker and Demerouti claimed that engagement is high when job and personal resources are adequate and job demands are in balanced [Bakker and Demerouti, 2008].

Engagement as originally proposed by Schaufeli et al. was used in the work context [Schaufeli et al., 2002b]. However, Schaufeli et al. showed that their proposed engagement is also meaningful for learners. In particular, they showed that higher vigor, a component of engagement, can lead to higher academic performance [Schaufeli et al., 2002a].

In this study, we used the definition of engagement proposed by Schaufeli et al. [Schaufeli et al., 2002a] to understand the engagement of learners engaged in distance PBL.

2.3 Measuring Engagement

Since engagement is an abstract concept, questionnaires were used to measure it. To measure engagement, Schaufeli et al. created the Utrecht Work Engagement Scale (UWES) with 17 questions focusing on vigor, deduction, and absorption [Schaufeli et al., 2002b]. UWES-S for students [Schaufeli et al., 2002a], UWES-9 with nine questions [Schaufeli et al., 2006], and UWES-3 with three questions [Schaufeli et al., 2017] have also been proposed.

Measuring engagement changes is challenging, as engagement changes daily [Breevaart et al., 2012, Sonnentag et al., 2010]. Engagement surveys are often conducted annually, making it difficult to track changes [Shami et al., 2015]. A decrease in engagement may decrease engagement in others [Mitra et al., 2017]. Thus, methods are required to measure engagement over short periods so that teachers can quickly detect declining learner engagement.

However, frequent surveys can burden respondents, necessitating alternative engagement measurement methods based on daily activities. For example, Kajiwara et al. measured work engagement using pulse and eye and body movements in a multimodal environment [Kajiwara et al., 2019]. To measure engagement in this study, we focused on daily activity reports in remote PBL.

2.4 Activity Report

Activity reports are used by teachers to track student progress or by students to consult with teachers. Chickering and Gamson argued that student-teacher contact and prompt feedback can improve undergraduate education [Chickering and Gamson, 1987]. Etkina and Harper's study of undergraduate education found that weekly reports help students solve problems quickly and reflect on their learning and help teachers adjust their teaching methods [Etkina and Harper, 2002]. Ito et al. found that weekly reports could be used to track student learning [Ito et al., 2016].

Activity reports are generally text based. Activity reports in remote work can be sent via text-based platforms such as email, Slack[1], Microsoft Teams[2], and other instant messaging apps [Lu et al., 2018]. Systems that use emojis to express emotions [Tang et al., 2022] and AI to present emotion analysis of text chats to participants [Nguyen et al., 2022] have been developed. Some studies have focused on enhancing communication by introducing chatbots [Benke et al., 2020a] and exploring the characteristics of effective remote teams based on text communication analysis [Cao et al., 2021]. These studies suggest that text-based activity reports support remote work.

Other studies used text activity reports to measure engagement. Tanaka et al. developed a learning model to estimate engagement based on text chat frequency and worker affiliation [Tanaka et al., 2021]. Shami et al. and Golestani et al. demonstrated that internal SNSs content can measure engagement [Shami et al., 2015, Golestani et al., 2018]. Cao et al. found that more exclusive words and second-person pronouns in text chats indicated better online team performance [Cao et al., 2021]. Wang et al. proposed a method for estimating user performance in Slack channels by analyzing messages and using content-independent features [Wang et al., 2022].

However, textual communication can induce negative emotions in users owing to a lack of nonverbal information [Hassib et al., 2017, Benke et al., 2020b]. Thus, we considered audio and video media. While voice can convey messages faster than text [El-Shinnawy and Markus, 1997], and can reduce the decision-making time when used in meetings accordingly [Suh, 1999], video is better for conveying intentions and emotions based on users' facial expressions, gestures, and facial movements [Veinott et al., 1999, Bänziger et al., 2009]. Because this study focuses on engagement, which indicates a mental state, we used video activity reports, which are more likely to convey mental information such as emotions.

2.5 Video Activity Report

He et al. studied an employee's engagement using video activity reports. Over two years, 418 reports were collected and analyzed, focusing on the employee's filled and silent pauses in the reports. The results showed that when engagement was high, filled pauses

[1] Where work happens | Slack, https://slack.com/ (Visited on January 31, 2023)
[2] Video Conferencing, Meetings, Calling | Microsoft Teams, https://teams.com/ (Visited on January 31, 2023)

were low; when satisfaction was high, filled pauses were short; when clarity was high, filled pauses were minor; and when job ratings were high, filled pauses were low and silent pauses were longer [He et al., 2020a]. This suggests that video activity reports, which include nonverbal information, may provide insights into engagement and other mental states.

He et al. studied video activity reports of students engaging in PBL, obtaining 232 reports from eight students over four months and interviewing six students. The learner comments suggested the availability of video activity reports in PBL [He et al., 2022]. He's analysis of nonverbal information in the reports showed that filled and silent pauses were related to engagement [He, 2022].

2.6 Filled and Silent Pauses

Filled and silent pauses are paralinguistic cues that express emotions and intentions [Fujisaki, 2004]. They are represented by pitch, intensity, and speech ratio, among others [Johar, 2014]. Some studies examined emotion estimation using paralinguistic cues [Delaborde and Devillers, 2010, Wang and Hu, 2018].

Christenfeld and Creager suggested that filled pauses occur when a speaker's thought process cannot keep up with their speech process [Christenfeld and Creager, 1996]. Goto et al. claimed that speakers employ filled pauses to make time for the next utterance to develop and maintain the conversation and that filled pauses express unconscious mental or thought states, such as self-confidence, hesitancy, anxiety, or modesty [Goto et al., 1999]. Filled and silent pauses are influenced by a speaker's levels of confidence and anxiety [Pope et al., 1970]. When the speech content is more abstract, speakers have more filled and silent pauses [Rochester, 1973]. When the speech content is more complex, the speaker needs longer time to start speaking [Brennan and Williams, 1995]. Moreover, filled and silent pauses are also affected by the situation. Filled pauses are common in interviews but not in speeches [Duez, 1982, Duez, 1985]. More silent pauses occur in stressful environments than in non-stressful ones [Buchanan et al., 2014].

These studies have shown that filled and silent pauses reveal a speaker's mental state. We explored if the pauses can be used to understand learner engagement.

3 Method

3.1 Research Questions

This study aims to support communication between teachers and students in distance PBL based on learner engagement. Learner engagement is related to task performance and dropout risk. Therefore, it is preferable for teachers to focus on learner engagement. However, it is difficult to measure engagement remotely due to the fewer communication opportunities than in face-to-face environments. A system is required to help teachers understand learner engagement in distance learning.

This study constructs a mechanism for teachers to understand learner engagement in distant environments. It is necessary to identify the factors that teachers should focus on in order to understand learner engagement. Therefore, this study focuses on video activity reports to understand learner engagement. An activity report is a teacher-student communication tool used in distance learning, which is usually sent via text. Video activity reports contain nonverbal information related to learner mental state and engagement.

We analyzed the video activity reports obtained by He et al. [He et al., 2022] of students engaged in PBL in a distance environment to investigate the relationship between the reports and engagement. Focusing on two types of information obtained from video activity reports, that is, verbal and nonverbal, we set the following research questions:

RQ1: How does learner engagement relate to verbal information within video activity reports?

RQ2: How does learner engagement relate to nonverbal information within video activity reports?

RQ1 focuses on the relationship between verbal information and engagement in video activity reports. Previous studies on video activity reports have not focused on report content [He et al., 2020a, He et al., 2022, He, 2022]; thus, it is essential to investigate how report content impacts engagement.

Engagement decreases in negative mental states. A person using negative statements has negative emotions [Kahn et al., 2007]. Therefore, we focused on negative words or phrases in video activity reports. We formulated the following hypothesis for RQ1:

H1: Negative statements in video activity reports indicate declining learner engagement.

RQ2 focuses on the relationship between nonverbal information and engagement in video activity reports. He et al. studied filled and silent pauses in employee reports. Filled pauses are related to the speaker's mental state [Goto et al., 1999], and silent pauses can be caused by mental stress [Lee et al., 2017]. Both pauses may be related to users' engagement.

The previous study analyzed the video activity reports of only one participant, so its conclusions are not generalizable [He et al., 2020a]. Our study analyzed video activity reports from eight students to examine the relationship between filled/silent pauses and engagement. We formulated the following hypotheses for RQ2:

H2-1: Occurrence of filled pauses in video activity reports relates to engagement.

H2-2: Occurrence of silent pauses in video activity reports relates to engagement.

3.2 Video Activity Report and Engagement Score

This section describes the collection of video activity reports [He et al., 2022].

3.2.1 Participants

The Ethics Committee on Library, Information and Media Studies at University of Tsukuba approved the previous study (No. 20-32) [He et al., 2022]. The experiment collected video activity reports and used snowball sampling on SNS (WeChat[3] and LINE[4]) to recruit eight male graduate students aged 23–26, as shown in Table 1.

[3] WeChat - Free messaging and calling app,https://www.wechat.com/ (Visited on January 31, 2023)

[4] LINE ｜ always at your side., https://line.me/en/ (Visited on January 31, 2023)

Participant	Age	Gender	Nationality	# of submitted reports / Actual trial days
P1	23	Male	Chinese	56 / 63
P2	25		Chinese	23 / 24
P3	25		Chinese	33 / 36
P4	25		Chinese	33 / 34
P5	23		Chinese	37 / 37
P6	24		Chinese	16 / 16
P7	26		Chinese	16 / 16
P8	23		Japanese	18 / 26

Table 1: Participants of the study

No.	Factor	Content
1	Vigor	When I'm doing my work as a student, I feel like I am bursting with energy.
2	Dedication	I am enthusiastic about my studies.
3	Absorption	I am immersed in my studies.

Table 2: Questionnaire items

We verified that, at minimum, non-native Japanese speakers could communicate in Japanese at the N2 level of the Japanese-Language Proficiency Test[5] and could easily report their activities in Japanese.

All participants engaged in PBL remotely, similar to teleworking, during their participation period. In this experiment, participants were asked to submit a video activity report of their activities and answer a questionnaire to measure their engagement every weekday. Only when participants submitted a video activity report and a response to the questionnaire were they paid a gratuity of 100 yen per day. Table 1 presents the number of times the participants submitted the data during their participation in the experiment. The experiment was conducted between August 2020 and November 2020.

3.2.2 Engagement Score

To measure engagement, we used the UWES-3 questionnaire proposed by Schaufeli et al. [Schaufeli et al., 2017], as it has the fewest questions, making daily surveys less burdensome. Because the UWES-3 was designed for company workers, the wording of some of the UWES-3 questions was changed by referring to the UWES-S questionnaire, an engagement measurement questionnaire for students [Schaufeli et al., 2002a]. Table 2 shows the actual questions.

The participants answered each question on a scale of 0 to 6 (0=never, 6=always). The average of the three questions was defined as the "engagement score" for the day, which we used in our analysis.

[5] JLPT Japanese-Language Proficiency Test, https://www.jlpt.jp/e/) (Visited on January 20, 2023)

Figure 1: A screenshot of a submitted video report

3.2.3 Procedure

During the experiment, the participants were asked to submit a video activity report and answer the questionnaire on weekdays, excluding holidays. They were given the following instructions:

– Your video activity report should be taken with your laptop, smartphone, or any other device with a microphone and camera.

– Any objects that mask your face should not be worn, and the video should be taken in a bust shot. (Figure 1 shows a screenshot of the actual video submitted)

– The report's content should be related to your study or research, such as what you learned in the day's lectures, how they prepared your reports, and the progress of your research.

– There is no limit to the length of each video. Each video will be approximately 30 seconds long, but it is acceptable for the video to be shorter or longer than 30 seconds.

– There are no restrictions on where you take video, but try to record in a place that is as quiet as possible. In addition, ensure that your voice is clear.

This procedure was based on the previous study in which similar video activity reports were collected [He et al., 2020a].

We asked participants to record a video activity report per day for two reasons. First, other studies that focused on activity reports also collected daily reports (e.g., [Pogorilich, 1992, Lu et al., 2018]). Second, engagement may vary from day to day [Breevaart et al., 2012, Sonnentag et al., 2010].

We set a guideline of 30 seconds as the length of each video activity report based on a trial conducted by the experimenter without recording time limitation in advance, which resulted in an average of approximately 30 seconds.

Participants were asked to take a video activity report and answer the questionnaire after recording the report every weekday. They uploaded the recorded videos once a

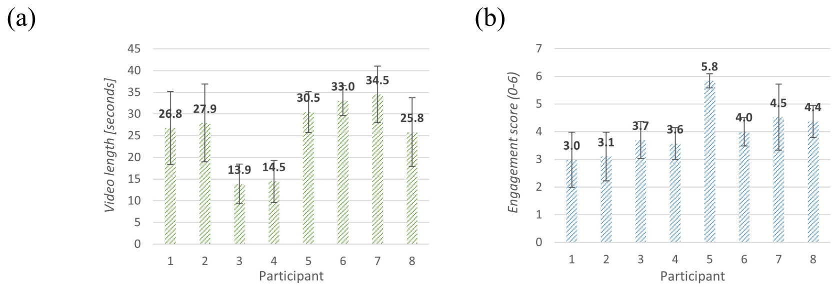

Figure 2: (a) Average length of video reports / (b) Engagement score. Error bars on each graph show the standard errors.

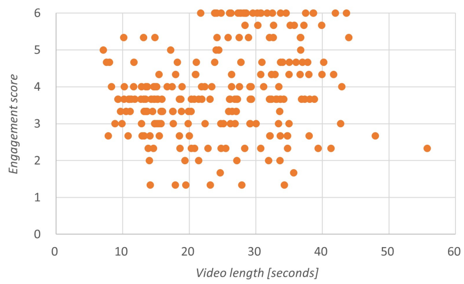

Figure 3: Relationship between engagement score and length of video activity reports

month to cloud storage. The engagement score for the day was calculated based on the answers to the questionnaire and was collected with the same day's video activity report.

In addition, participants were asked to continue participating in the experiment for at least four weeks when they consented to the experiment. Four weeks after the start of the experiment, participants could withdraw from the experiment at any time.

4 Result

Table 1 lists the 232 video activity reports and questionnaire responses. Video activity reports and engagement scores were always collected together. We investigated the relationship between the video activity report and the engagement score on the same day. Participant participation ranged from 16 to 63 weekdays. Figure 2 shows the video activity report length and engagement score for each participant. The average video activity report was 24.8 seconds (SD: 9.6 seconds), with an average and median engagement score of 3.9 and 3.7 (SD: 1.2), respectively.

Engagement scores below the median were labelled "low engagement score," and those above the median were labelled "high engagement score." Of the 232 scores, 128 were classified as low engagement scores and 104 as high engagement scores.

4.1 Length of Video Activity Reports and Engagement Score

We investigated the relationship between the video length and engagement scores. Figure 3 shows a scatter plot of video length and engagement score. Pearson's correlation

My task is to create a system, but that is still **not** finished.
We tried to solve the problem we had last week, but we have **not** solved it yet.
My research is underway but **not** progressing very well.
I **cannot** give you concrete results.
I am not feeling well today, so I went to the hospital, and I **did not** perform any tasks.
I have looked for papers related to my research but have **not** found helpful ones.
The model was trained in an outdoor environment; therefore, it was found to be **less** accurate in an indoor environment.
I read the paper, but I am **not** very good at English, so I had to translate it and use online sites to complete it.
This analysis software is a bit **difficult** to use, and I am learning and analyzing various functions.
I tried to analyze the data, but still had **insufficient** data to analyze.

Table 3: Examples of negative expressions in video activity reports. ***Bolded phrases*** *indicate the basis for determining that the report was negative.*

coefficient was not high but correlated ($r = .22, t(230) = 3.46, p = .0006$).

Longer video activity reports were more possibly related to higher engagement scores.

4.2 Negative Statements and Engagement

We analyzed the engagement scores and content of the video activity report (RQ1).

We used Google Cloud Speech-to-Text API[6] to transcribe the participants' video reports into Japanese. All errors were manually corrected.

The labelers determined whether the video activity report included negative expressions or not. Table 3 lists several negative phrases that were found in the reports. A video activity report was labeled = negative if (1) a negating word for the verb of the sentence in which the student was the subject appeared once or (2) a generally negative or pessimistic term appeared. If no negative words appeared, the report was labeled as non-negative. In cases in which the judges of the two labelers differed, labeling was performed by consensus. Of the 232 video activity reports, 41 were labeled as negative and 191 as non-negative. The agreement rate was 99.6% with labelers only disagreeing on one case. We think the reason for this very high agreement rate was that enough detailed criteria were predetermined to avoid subjective differences in labeling.

Figure 4 shows the engagement scores when video activity reports labeled negative or non-negative were submitted. The average engagement score for reports labeled negative was 3.4 (SD: 1.2), and 4.0 (SD: 1.2) for reports labeled non-negative. Welch's t-test ($t(58) = -2.78, p = .007 < .01$ ($Cohen's\ d = 0.48$)) revealed a significant difference, suggesting that when a video activity report containing negative phrases was submitted, engagement on that day was lower than when a report containing no negative words was submitted.

This result supports hypothesis H1, "Negative statements in video activity reports indicate declining learner engagement."

[6] Speech-to-Text: Automatic Speech Recognition | Google Cloud, https://cloud.google.com/speech-to-text (Visited on January 20, 2023)

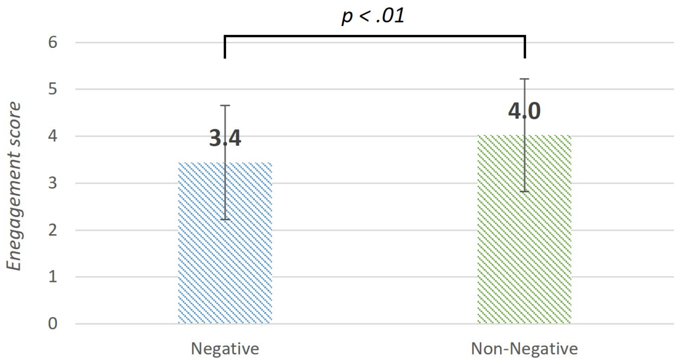

Figure 4: Average of engagement score on days when negative or non-negative video activity reports were submitted

4.3 Nonverbal Information and Engagement

The following analysis was conducted to clarify the relationship between learner engagement and nonverbal information in video activity reports (RQ2).

The experimenters manually labelled the video activity reports for filled and silent pauses. Based on previous studies [Goto et al., 1999, Campione and Véronis, 2002], typical Japanese fillers, such as /ee-/, /maa-/, and /ano-/, as well as those with the end of the word extended (e.g., /kyo wa-/ ("Today...")), were labelled as filled pauses. Silent pauses lasting for more than one second after the end of the utterance were labelled. ELAN[7] was used for labelling.

Table 4 lists the items analyzed for nonverbal information. The frequency, average length per minute, and length per time were calculated for filled and silent pauses.

Figure 5 shows the frequency and time per minute of filled pauses and time per filled pause for the days with low and high engagement scores (N=232). We compared whether there was a difference in filled pauses between the days with low and high engagement scores.

The frequency of filled pauses (Figure 5(a)) averaged 11.3 times/minute (SD: 6.1 times/minute) for the days with low engagement scores and 9.3 times/minute (SD: 7.7 times/minute) for the days with high engagement scores. Welch's t-test showed that $t(194) = 2.17, p = .03 < .05$ $(Cohen's\ d = 0.29)$, indicating a significant difference.

The average length of filled pauses per minute (Figure 5(b)) was 5.0 seconds (SD: 3.4 seconds) on average for the days with low engagement scores and 3.6 seconds (SD: 3.3 seconds) for the days with high engagement scores. Welch's t-test showed that $t(223) = 3.29, p = .001 < .01$ $(Cohen's\ d = 0.43)$, indicating a significant difference.

Furthermore, the average length of filled pause per time (Figure 5(c)) was 0.5 seconds (SD: 0.3 seconds) for the days with low engagement scores and 0.4 seconds (SD: 0.3 seconds) for the days with high engagement scores. Welch's t-test showed that $t(931) = 4.24, p < .01$ $(Cohen's\ d = 0.27)$, indicating a significant difference.

These results support hypothesis H2-1, "Occurrence of filled pauses in video activity report relates to engagement." Specifically, the number or duration of filled pauses per

[7] ELAN | The Language Archive, https://archive.mpi.nl/tla/elan (Visited on January 31, 2023)

Item	Definition	Unit	Average (SD)
Frequency of filled pauses	Number of filled pauses per minute in each video activity report	times/minute	10.4 (6.9)
Length of filled pauses	Length of filled pauses per minute in each video activity report	second	5.0 (3.2)
Length of each filled pause	Length of filled pauses per time	second	0.4 (0.3)
Frequency of silent pauses	Number of silent pauses per minute in each video activity report	times/minute	2.6 (3.5)
Length of silent pauses	Length of silent pauses per minute in each video activity report	second	8.3 (4.7)
Length of each silent pause	Length of silent pause per time	second	1.5 (0.5)

Table 4: Measured non-verbal information

minute or the duration per time was greater in video activity reports on days with low engagement scores than on days with high engagement scores.

Figure 6 shows the frequency and time per minute of silent pauses and time per silent pause for the days with low and high engagement scores (N=232). We examined whether there was a difference in the occurrence of silent pauses between days with low and high engagement scores.

The frequency of silent pauses (Figure 6(a)) averaged 1.6 times/minute (SD: 3.0 times/minute) for the days with low engagement scores and 3.8 times/minute (SD: 3.8 times/minute) for the days with high engagement scores. Welch's t-test showed that $t(192) = -4.82, p < .01$ $(Cohen's\ d = 0.65)$, indicating a significant difference.

The average length of silent pauses per minute (Figure 6(b)) was 2.4 seconds (SD: 4.4 seconds) for the days with low engagement scores and 5.8 seconds (SD: 5.6 seconds) for the days with high engagement scores. Welch's t-test showed that $t(191) = -5.16, p < .01$ $(Cohen's\ d = 0.69)$, indicating a significant difference.

Furthermore, the average length of silent pauses per time (Figure 6(c)) was 1.4 seconds (SD: 0.5 seconds) for the days with low engagement scores and 1.6 seconds (SD: 0.5 seconds) for the days with high engagement scores. The Welch's t-test of $t(166) = -1.62, p = .11$ $(Cohen's\ d = 0.21)$ showed no significant difference.

Thus, hypothesis H2-2, "Occurrence of silent pauses in video activity report relates to engagement" is supported. Specifically, reports with low engagement scores had fewer or shorter silent pauses per minute than those with high engagement scores did.

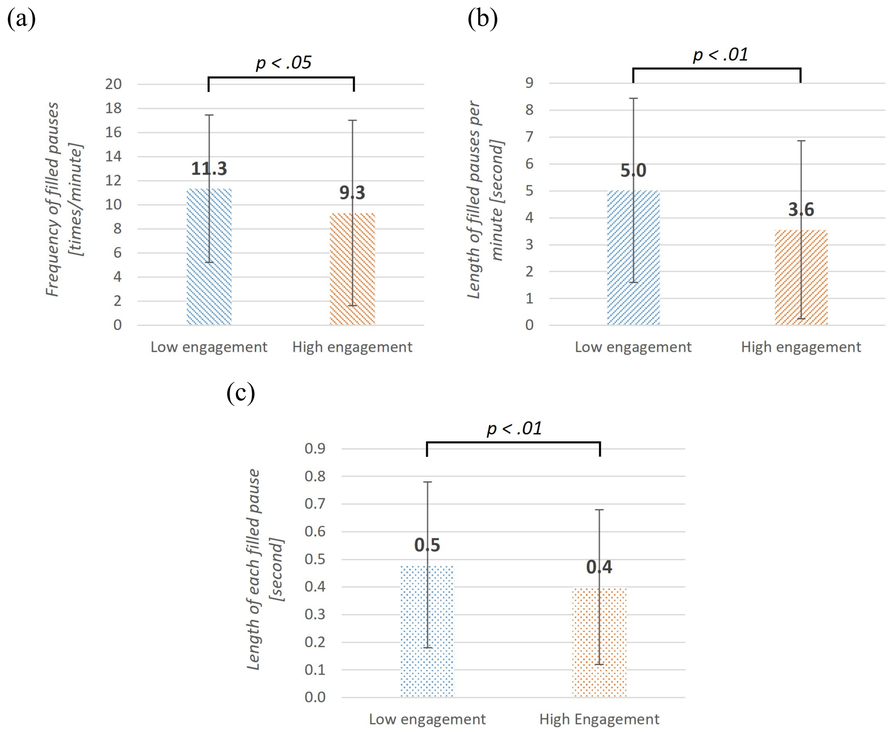

Figure 5: (a) Frequency of filled pauses of two groups based on engagement score. (b) Length of filled pauses of the two groups. (c) Length of each filled pause of the two groups

5 Discussion

This study will create a framework to help teacher-student communication by understanding learner engagement in distance learning. This chapter summarizes the findings, introduces a system prototype, and describes the study's limitations and future research.

5.1 Findings

Based on the results, the answers to the research questions are summarized as follows. The answer to RQ1, "How does learner engagement relate to verbal information within video activity reports?" is that when negative phrases were included in the video activity report, learner engagement was lower than when negative phrases were not included in the video activity report.

The answer to RQ2, "How does learner engagement relate to nonverbal information within video activity reports?" is that video activity reports on days with low engagement scores had a greater number or longer duration of filled pauses or a smaller number or shorter duration of silent pauses per minute than those on days with high engagement scores.

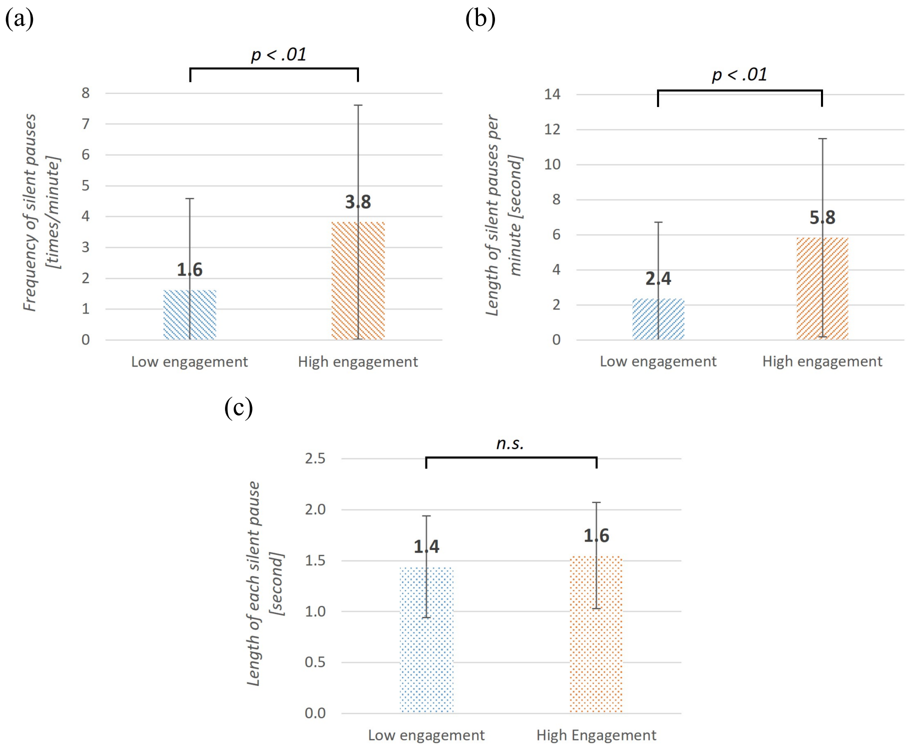

Figure 6: (a) Frequency of silent pauses of two groups based on engagement score. (b) Length of silent pauses per minute of the two groups. (c) Length of each silent pause of the two groups

These findings are useful for building a system that uses video activity reports to understand learner engagement. For instance, if the system identifies negative phrases or frequent filled pauses, it indicates a decline in engagement.

Filled and silent pauses are affected by cognitive, mental, and speech situation, and it is difficult to determine whether these factors are positively or negatively correlated. We observed graduate students engaged in PBL, which is based on research activities, and recorded their reports. We discovered that when learner engagement was low, filled pauses were more frequent or longer and silent pauses were infrequent or shorter. The reasons for these are not yet known, but a possible explanation might be that during the video activity report, students employ filled pauses when thinking of what to say and use silent pauses when nothing to say [He et al., 2022].

A small positive correlation was found between video activity report length and engagement score. It is possible that activity reports become longer due to an increase in the number of items students want to report as the learning activity progresses, which could indicate high engagement. Additionally, whether and how much the length guideline of 30 seconds that was given to the participants affected engagement can be examined in the future.

5.2 Classification of Activity Reports Toward Automated Engagement Estimation

We labeled a report as negative if one negative term was found. This judgement may be easy to implement for a support system. Consider the following report obtained in this study, for example.

> *Today, I continued a survey on OpenFace [an analysis toolkit]. I sought to determine how the data from OpenFace could be used. We received a lot of data from OpenFace, so I will continue to investigate this because I* ***do not yet*** *know which parts of the data can be effectively used in my research. That is all.* (P1)

This report was labeled as negative according to the phrase "**do not yet**". However, this does not necessarily mean the report itself has a negative tone.

As a step toward automated engagement estimation that would work in an support system, we also conducted a preliminary automated sentiment analysis of the reports to investigate current applicability of the analysis method. We implemented a standard sentiment analysis program using BERT [Devlin et al., 2019], a natural language model widely used today for natural language processing; cl-tohoku/bert-base-japanesewhole-word-masking[8], a standard pre-trained Japanese BERT model to tokenize words to input into BERT; and a standard fine-tuned Japanese sensentiment analysis model, koheiduck/bert-japanese-finetuned-sentiment[9], which classifies sentence as POSITIVE, NEGATIVE, or NEUTRAL.

Of the 232 activity reports, 128 were classified as POSITIVE, 13 as NEGATIVE, and 91 as NEUTRAL as a result. Considering negative reports, 39 were labeled negative by the labelers but not by automated sentiment analysis, 11 were judged negative by automated analysis but not by the labelers, and two were judged negative by both. Machine learning judgments of the reports differed significantly.

The accuracy of the automated sentiment analysis should be mentioned. Reports judged as NEGATIVE by sentiment analysis include the following:

- *Today, I was working on English slides for my CollabTech [an international conference] presentation. My current progress is that I completed half of the slides on the research background. I plan to complete all of it by the end of this week. That's all.* (P1)
- *Today, I sorted out the questions I received at the workshop and other mentions on the form that were not asked during my presentation.* (P2)
- *Today, I attended the seminar and got advice from the professor on how to survey and on the main points [for my research].* (P4)

These examples are classified as NEGATIVE in the automated analysis, although they do not seem to be negative in their meanings. It is still difficult to analyze sentiments automatically in Japanese activity reports.

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[8] https://huggingface.co/cl-tohoku/bert-base-japanese-whole-word-masking (Visited on August 16, 2023)

[9] https://huggingface.co/koheiduck/bert-japanese-finetuned-sentiment (Visited on August 16, 2023)

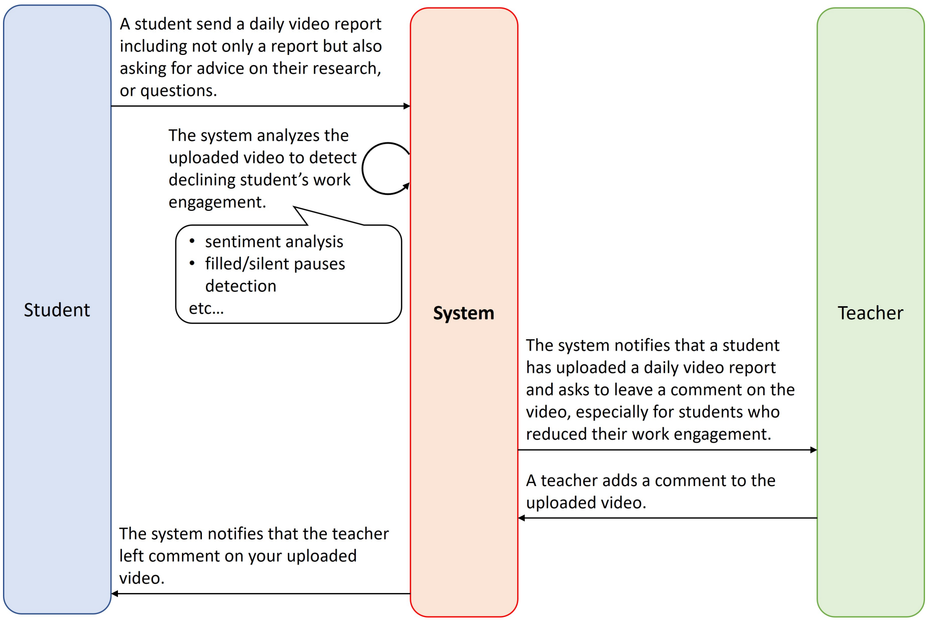

Figure 7: A communication system between a teacher and a student

5.3 Communication System Estimating of Engagement Using Video Activity Report

Figure 7 shows a web-based system for teachers to track learner engagement. Students upload video activity reports asking their teachers to comment. The student is notified when the teacher adds comments, allowing them to review the feedback.

A system prototype is shown in Figure 8 [He et al., 2020b]. This system allows remote communication between teachers and students, based on video activity reports. However, this system is unwieldly for teachers. Generally, teachers manage multiple students. Therefore, reviewing video activity reports and commenting on them requires a significant amount of time.

The results of this study can be used in this system. The system can detect students with declining engagement by automatically analyzing video activity reports. Notifying the teachers of such students allows them to focus on those who need more attention while saving time.

5.4 Considering How to Estimate Engagement with Greater Accuracy

This study focused on negative phrases, filled pauses, and silent pauses in order to measure engagement. Other factors, such as part-of-speech or the type of words, can also be considered as verbal information [Wang et al., 2022, Cao et al., 2021]. Nonverbal information can also be considered, such as speech style (e.g., inflection and volume), eye contact, and body movement. In addition, metadata, such as the time, frequency, and duration of report submission, can be focused on.

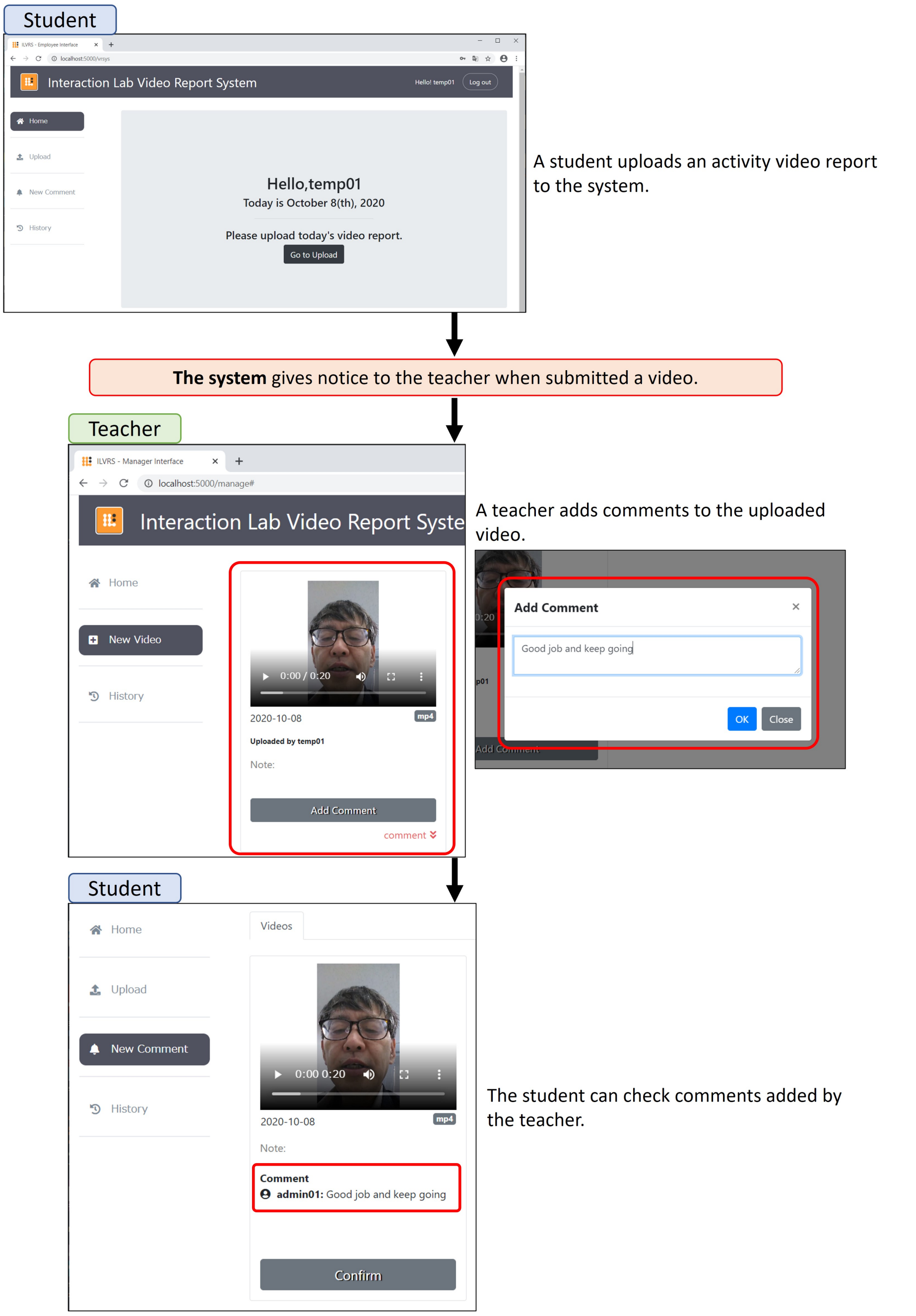

Figure 8: The prototype system

It is possible that estimating engagement with multiple factors could lead to more precise results, but manually determining the useful factors is time-consuming. AI technology, such as deep learning, can identify the features required for a more accurate engagement estimation.

In this study, we found that many filled pauses indicated low engagement but not always for all students. Therefore, to accurately measure engagement, individual user speech and body movements should be observed. In a system used by many students, AI technology can be used to understand individual behavior, which is difficult with human resources. AI can create a model for each user's behavior. When a user's actions deviate from this model, changes, such as decreased engagement, may occur. He et al. observed that students performed unusual movements in video activity reports, such as frequently lifting their head [He et al., 2022]. There is a possibility that unusual movements could indicate engagement. AI can learn a user's typical behavior, such as head movement, eye direction, and voice tone, from video activity reports to detect unusual movements.

In summary, AI technology can estimate learner engagement more accurately. Deep learning based on video activity reports can identify key features, such as negative phrases, filled pauses, or silent pauses. Additionally, a system that creates a model of each student's behavior to detect unusual actions can help estimate engagement based on their habits.

5.5 Limitation and Future Work

In this study, video activity reports obtained from eight students were analyzed. Because these eight students came from the same laboratory of the same major, the results might include biases accordingly. If students from different laboratories, genders, or nationalities participate, the results might be somewhat different.

Several future studies are needed to obtain a high level of engagement accuracy. The first is obtaining individual behavioral changes to reduce students' environmental differences. As Azevedo reported, using self-report measures alone is inadequate for measurement engagement [Azevedo, 2015]. AI technology helps understand individual behavior. For teachers to grasp learner engagement more accurately, it will be necessary to combine what this study has found with what AI reveals by focusing on each individual change in video activity reports. The second is to investigate the relationship between each component (Vigor, Dedication, and Absorption) and engagement. Based on this relationship, it could be possible to identify the factors that allow the estimation of engagement with high accuracy. The third is analysis of video information from the video activity reports. Sanghvi et al. and Rajavenkatanarayanan et al. claimed that body movements and facial expressions from videos can be used to measure engagement [Sanghvi et al., 2011, Rajavenkatanarayanan et al., 2018]. The unusual movement observed by He et al. [He et al., 2022] can also be considered for estimating engagement. By analyzing video information, also becomes possible to examine the differences in media used to measure engagement, such as audio and video.

6 Conclusion

This study is for supporting remote PBL with particular focus on communication between a teacher and students engaging in remote PBL. To create a mechanism for a teacher to understand students' engagement, we analyzed the relationship between the video activity reports from students and theier engagement, which has not been sufficiently addressed.

From video activity reports submitted once a day from eight graduate students majoring in informatics, we found that engagement decreased (1) when the reports contained negative words, (2) when filled pauses were frequent or long, and (3) when silent pauses were infrequent or short. In addition, we developed a prototype system and discussed the design guidelines for a system using AI technology to estimate engagement considering individual differences and to assist in understanding learner engagement.

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