Exploring Eye-tracking Features to Understand Students' Sensemaking of Learning Analytics Dashboards

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Abstract

Learning analytics dashboards (LADs) are widely used in learning analytics as visual tools to present information about learning activities and outcomes. However, only few studies have explored how students make sense from LAD elements and what cognitive processes follow after viewing each element. In this study, we explore how eye-tracking data can help researchers to identify salient LAD elements critical to students' sensemaking process. Our findings reveal that the eye-tracking derived features, including fixation duration and eye movement patterns, are highly indicative of students' social comparison tendencies and offer valuable insights into their sensemaking processes.

CCS Concepts

• **Human-centered computing** → *HCI theory, concepts and models*; • **Applied computing** → *Education*.

Keywords

learning analytics dashboards, eye tracking, sensemaking, motivation

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1 Introduction

Learning Analytics can be defined as a process in which educational and learning-related data is collected and analyzed to improve learner outcomes and enhance the overall learning experience [6]. LA is strongly connected to a variety of fields, including education, technology, psychology, and social sciences [9]. Learning analytics dashboard (LAD), a commonly used outcome of LA research, is a visual representation of the information extracted from learners' behaviour, learning processes, and learning context(s) [22]. There is evidence that LADs can stimulate cognition, emotion, and motivation [17]; however, research on how this happens is scarce. In this exploratory study, we examine to what extent eye-tracking systems, a popular apparatus used to study cognition, emotion, and motivation [30], can help us understand the processes that unfold during students' viewing of LADs.

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2 Background and Research Questions

2.1 Learning Analytics Dashboards

Learning analytics dashboards are among the first LA deployments aiming to provide students with means of awareness, reflection, motivation, and induce behavioural change [29]. However, a recent mapping study by [17] pointed out the unconvincing evidence of LADs' effectiveness, citing several factors, including the way the LADs are studied, often comparing outcomes of LAD users and non-users. Such a comparison confounds the LAD effect with LAD engagement, and it makes it difficult to understand the underlying mechanism of how dashboards influence students' reflection and motivation. We posit that a more nuanced approach to studying and designing LADs is needed to advance our understanding of how LADs impact individual learners. In our view, this requires pursuing research in two directions: 1) understanding the role each dashboard element and its framing has on learners, and 2) how the elements' impacts change with students' individual characteristics.

LADs consist of information elements, which are typically derived from traces of students' activity in LMS, such as counts of logins and file access [18, 19], participation in the forums in terms of counts [25, 32] or social engagement with peers [11, 27]. To make sense of the presented values in LAD elements, LADs show students additional information, i.e. frame of reference [33], such of their peers [13]. As students pursue different achievement goals [23] when they study, same information in LAD may impact students differently [25]. To date, majority of research evaluates LADs as a blackbox, not considering how student react to concrete information presented in LAD. Similarly, statistical methods used examine central tendency, without studying underlying variance from the perspective of students differences. Aghaei et al. [2] used a different approach, studying how alternating framing of LAD elements (time spent and ability), with varied combination of values, modified students' attributions to causes of success/failure, emotions, and motivation.

Various research designs are used to study LADs: laboratory settings allow to tightly control LAD's content (e.g., [2, 3]), field randomized studies allow drawing causal conclusions [10], and participatory approaches with learners aim to capture learners preferences via workshop activities [7], or by letting them customize LAD elements [14]. Although all studies can view dashboards at different levels of granularity in terms of LAD elements, they rarely focus on which LAD elements students attended to and what processes unfolded afterward.

The novelty of this study is in studying students' engagement with LAD elements during their sensemaking process and exploring how eye-tracking can reveal critical elements shown in LAD for determining its impact on individuals.

2.2 Eye-tracking and Sensemaking Mechanism in LADs

An eye-tracking system can be defined as a monitoring tool capable of recording a combination of gaze points, fixation duration, and changes in pupil size [21]. Eye-tracking data can be used to evaluate users' mental state, level of attention, cognitive load, and emotions [12, 21]. For example, in the education and learning domains, eye-tracking data was utilized to improve users' motivation and learning [24], enhance self-regulated learning [5], and boost students' problem-solving ability [4].

Eye tracking is already a well-established research tool in LAD research, however its use in LAD research is fairly limited. Jo et al. [15] found that students who viewed text part of graphs in LAD more frequently and longer had higher comprehension levels than thsoe who focused on the graphical parts. Vatrapu et al. [28] examined nine visual representations and found that those showing average performance received more attention than the strong and weak performance representations, and that students focused on areas with greater variance in information. These studies used cumulative measures such as heatmaps and gaze duration for areas of the LAD and did not examine the information content of LAD elements students focused on.

2.3 Study Context and Theoretical Background

This study analyzes eye-tracking data collected in our prior study [1], which we briefly summarize here. Weiner's Attributional Theory of Motivation and Emotion[31] states that when presented with outcomes of achievement activity (e.g., assignment grade), students attribute the outcome to a cause(s) they select. The nature of the cause determines if it positively or negatively impacts emotion and motivation. For example, the cause "I did not spend enough time" is internal to the student, unstable and controllable by the student, and may elicit guilt (negative activating emotion [20]), and motivates students to work harder. However, an attribution to the lack of ability is maladaptive, as it is considered internal/stable/uncontrollable ("I am dumb"). We used peer frame of reference [13, 33], we studied how displaying peers performing better/same/worse affects students' attributions to causes, and their emotions and motivations. In the qualitative laboratory study, we presented participants with dashboard variants and captured their sensemaking process using a talk-aloud protocol, which was later coded following the theoretical framework above. During the lab sessions, we have also captured eye-tracking data, which we explore in this study.

2.4 Present Study and Research Questions

In this exploratory study, we study the utility of eye-tracking technology to advance our understanding of how LAD elements contribute to students' sensemaking and student motivation. By analyzing eye-tracking data, we aim to identify which elements in the dashboard draw participants' attention the most and how they relate to their sensemaking process and motivational responses. We also examine how students individual Achievement Goal Orientations (AGO) [8] influence students' interactions with LADs. Specifically, we aim to answer the following research questions:

- **RQ1**: Can eye-tracking derived features (gaze duration and eye movement patterns) identify the most notable LAD elements during students' sensemaking process while viewing LADs?
- **RQ2**: Can eye-tracking features (gaze duration and eye movement patterns) derived from students' engagement with LADs determine students' motivation?

3 Methods

3.1 Data Collection Procedure

The dataset analyzed in this study originates from our prior qualitative study exploring students' attributions, emotions, and motivation in response to seven dashboard prototypes with varying social comparison framing [1]. Figure 1 shows a dashboard example. Students were asked to imagine that each dashboard presented their assignment performance on the two-week assignment in the programming course they were familiar with, showing their grades and the grades of six peers. The peers' grades were all higher, the same, or lower than the student's grade. Secondary information included with the grades was either the time spent on the assignment (in the Time Dashboards) or the students' programming ability (in the Ability Dashboards, see Figure 1). Secondary information was higher or lower than the student's, creating six dashboard variants in each group (see the Description column in Tables 1a and 1b). The "Full" dashboards included grades, time spent, and ability for all; the values were both below and above the student's values.

In a laboratory setting, after filling out demographics and AGO questionnaires and eye-tracker calibration, the participants were presented with a sequence of Ability (labelled A1-6) or Time (T1-6) dashboards, followed by the Full Dashboard (AF or TF). For each dashboard, they were given time to make sense of the dashboard without the interviewer's interruption ('sensemaking period'), after which the interviewer asked questions about students' understanding of their performance, why they thought they achieved this result, how they were feeling about the outcome, and how motivated they were for the next assignment. They were also asked to identify with which peer they compared the most. The interview was captured in both audio and video formats, transcribed, and coded by two coders ($\kappa = 0.68$) based on Weiner's attributional theory [31] and Pekrun's Control-value Theory [20]. In this study, we used only the motivational outcome codes for the participants.

3.2 Participants and Achievement Goal Profiles

39 undergraduate students (25 women, 12 men, one non-binary, one not specified; all 18-30) from research-intensive Canadian universities were divided into the Ability group ($n = 19$) and Time group ($n = 20$). Their Achievement Goal Profiles were determined using a hierarchical clustering algorithm (`hclust` in R, Ward's method, Euclidian distance) on the mastery, performance-approach, and performance-avoidance subscales of PALS questionnaires as follows: Cluster 1: high mastery and low performance-avoidance, Cluster 2: high mastery and high performance-avoidance, and Cluster 3:

Figure 1: An example of ability dashboard showing higher grades and higher ability. The bounding box of one of the AOIs displayed by a red frame.

low mastery, low performance-approach, and middle performance-avoidance. For details, see [1].

3.3 Eye-tracking Data and Preprocessing

Eye-tracking data were captured using the GP3HD V2 eye tracker, which operates at a sampling frequency of 60 Hz. Out of 51 features extracted by the eye tracker's API, we used four which were relevant to our analysis: relative time passed from the beginning of the recording session, X and Y position of the eye gaze on the screen (converted to values between 0 and 1), the duration of the gaze, and an identifier of the gaze.

Areas of Interest (AOIs) were defined within the dashboards using bounding boxes around LAD elements representing the participants and peers (red boxes s1-s7 in Figure 1). The dashboards contained seven AOIs, representing the student's grades and their time spent or ability level. Areas outside of AOIs were classified as being 'elsewhere.' Next, each gaze point was labelled with the AOI by mapping their respective coordinates. For statistical analyses, each AOI fixation was represented as categorical data using one-hot encoding.

The features in our dataset were categorized into three major groups: eye-tracking, AOIs, and qualitatively coded features. Eye-tracking features included gaze information such as gaze location and duration. AOI features described the specific LAD element that the participant was fixating on. Qualitatively coded features included data on students' motivation.

We analyzed only data from the sensemaking period, an interval when participants were presented with the dashboard and started interacting with the interviewer. First, for all the dashboards, we extracted the time each participant fixated on each AOI. To allow for comparisons between participants, we transformed absolute gaze time values into percentages, as sensemaking time varied among participants. To study the sensemaking process, we have extracted sequences of AOI fixations of length three with an A-B-A pattern, which may represent comparisons between two LAD elements.

3.4 Statistical Analyses

To answer our research questions, analysis of variance (ANOVA) and Tukey's Honest Significant Difference (HSD) were performed to investigate significant differences among participants in each Achievement Goals cluster. ANOVA and Tukey's HSD test were also used to explore differences between means of time portions of each peer on each dashboard at a 95% confidence level.

In addition, multiple T-tests were administered to find statistically significant differences between motivated and demotivated participants.

Table 1: Description of each dashboard and the characteristics of the most compared-with and second most compared-with peers. Indicators: G grade, T time, A ability, relative levels: ˆ higher, ˆˆ highest, _ lower, __ lowest, = similar, and ˜ closest, e.g. ˆˆ AOI with the highest grade in LAD.

Table 1a: Ability dashboards descriptions

Dashboard	Description	Most Compared	Second Most Compared
A1	Higher Grade + Higher Ability	14, s5 (ˆG,=A)	3, s1 (ˆG,ˆˆA)
A2	Higher Grade + Lower Ability	10, s5 (ˆG,=A)	4, s1 (ˆG,__A)
A3	Similar Grade + Higher Ability	8, s2 (=G,ˆˆA)	6, s6 (ˆˆG,__A)
A4	Similar Grade + Lower Ability	8, s3 (ˆˆG,ˆˆA)	7, s4 (ˆG,=A)
A5	Lower Grade + Higher Ability	10, s6 (ˆˆG,__A)	4, s5 (__G,ˆˆA)
A6	Lower Grade + Lower Ability	12, s3 (ˆˆG,ˆˆA)	5, s2 (_G,=A)
AF	Mixed	7, s6 (ˆˆG,˜_T,=A)	6, s2 (ˆG,ˆˆT,ˆˆA)

Table 1b: Time dashboards descriptions

Dashboard	Description	Most Compared	Second Most Compared
T1	Higher Grade + Higher Time	15, s4 (˜ˆG,=T)	3, s5 (ˆˆG,ˆT)
T2	Higher Grade + Lower Time	8, s5 (ˆG,=T)	7, s4 (ˆG,__T)
T3	Similar Grade + Higher Time	6, s2 (=G,_T)	4, s1 (__G,=T)
T4	Similar Grade + Lower Time	10, s2 (ˆˆG,ˆˆT)	5, s3 (ˆG,__T)
T5	Lower Grade + Higher Time	14, s5(ˆˆG,˜_T)	2, s4 (_G,ˆˆT)
T6	Lower Grade + Lower Time	14, s3 (ˆˆG,˜ˆT)	1, s1 (_G,__T)
TF	Mixed	8, s6 (ˆˆG,˜_T,=A)	4, s2 (ˆG,ˆˆT,ˆˆA)

4 Results

4.1 Self-reported Influential LAD Elements

Table 1 shows the most compared-with and the second most compared-with peers in LADs as reported by participants during the interview, including the counts of the participants and peers' characteristics.

4.2 Gaze Time and Peers' Characteristics

Table 2 shows the mean proportion values of each participant's duration fixated on the peers for the Time and Ability groups, respectively. In this table, s0 indicates elsewhere, s1-s6 are the peers, and s7 represents the participants themselves. The last column shows ANOVA p-values and the significant pairwise comparison for TukeyHSD post hoc tests.

The result of ANOVAs on gaze time portions spent on each peer (i.e., AOIs in Figure 1) on each dashboard showed a significant difference in the gaze duration for all dashboards ($p < 0.05$). Therefore, a post hoc TukeyHSD test was performed; notably, only in T1 and A1, the gaze duration for s7 (the participants themselves) was significantly different from peer comparators other than s2 ($p < 0.05$), as A1 and T1 were first LADs where participants saw their values in s7, which was unchanged in the later LADs in the sequence.

4.3 Motivation and Clusters

Table 3 shows the number of motivated and demotivated participants for each dashboard overall and separated by AGO clusters. As some participants were neither motivated nor demotivated, the sum of motivated and demotivated participants does not necessarily add up to the total number of participants in time and ability groups. Also, in some cases, participants reported being both motivated and demotivated.

To analyze the differences among clusters, ANOVAs were performed on different sub-classes of the data set. Firstly, ANOVAs were performed on time portions for each cluster, and the result indicated a significant difference in dashboard T6 for s4 ($p = 0.031$, statistic = 4.39). The TukeyHSD test revealed a significant difference between Clusters 1 and 3 ($p = 0.025$, z-score = 6.375).

Although the T-tests indicated significant differences between motivated and demotivated participants for the gaze time proportion of certain peers on some dashboards, the results are not reported due to the small sample sizes in these groups, which may limit the reliability of the findings.

4.4 Sequences

We used the harmonic mean of the occurrence of the sequence and the number of participants having that sequence as a weight metric to consider the effects of both of these elements when comparing the frequent sequences. The most frequent comparison sequences (sorted by weight) of length three in each dashboard (with pattern A-B-A) are shown in Table 4. The sequences containing s0 (elsewhere) are not reported as they do not represent a valid comparison pattern.

Table 2: Combined mean percentage values of each participant's fixation duration on peers across Time (T1-TF) and Ability (A1-AF) groups. s2 times not considered for analysis because of 'central fixation bias' (see Discussion section). Bold indicates the highest gaze time while disregarding s2 due to the central fixation bias and s7 representing self. Underlined are those AOIs the participants compare with the most, as per Table 1.

Dashboard	s0	s1	s2	s3	s4	s5	s6	s7	p value
A1	11.64	11.76	16.06	9.99	7.26	**13.13**	7.89	22.28	$<0.001^{s1/s7,\ s2/s4,\ s2/s6,\ s3/s7,\ s4/s7,\ s5/s7,\ s6/s7}$
A2	9.65	13.24	16.17	10.62	7.86	**13.86**	9.06	19.53	$<0.001^{s2/s4,\ s3/s7,\ s4/s7,\ s6/s7}$
A3	9.79	**13.72**	19.07	11.74	8.15	11.89	8.96	16.67	$<0.001^{s2/s3,\ s2/s4,\ s2/s5,\ s2/s6,\ s4/s7,\ s6/s7,}$
A4	11.72	10.82	15.04	**15.61**	11.44	10	9.18	16.2	$<0.001^{s3/s6,\ s5/s7,\ s6/s7,}$
A5	10.91	12.19	20.76	9.84	7.83	11.02	**12.68**	14.77	$<0.001^{s1/s2,\ s2/s3,\ s2/s4,\ s2/s5,\ s2/s6,\ s4/s7,}$
A6	10.14	10.1	18.65	**18.82**	7.38	9.95	10.2	14.76	$<0.001^{s1/s2,\ s1/s3,\ s2/s4,\ s2/s5,\ s2/s6,\ s3/s4,\ s3/s5,\ s3/s6}$
AF	8.4	10.2	15.94	9.64	**13.67**	12.27	12.92	16.96	$<0.001^{s1/s2,\ s1/s7,\ s2/s3,\ s3/s7}$
T1	5.93	**15.18**	16.6	10.34	9.67	10.05	9.45	22.78	$<0.001^{s1/s7,\ s2/s3,\ s2/s4,\ s2/s5,\ s2/s6,\ s3/s7,\ s4/s7,\ s5/s7,\ s6/s7}$
T2	7.14	**13.08**	17.75	11.69	11.55	12.6	9.42	16.78	$=0.002^{s2/s6\ ,s6/s7}$
T3	11.31	11.55	16.93	13.4	10.19	**13.05**	7.84	15.74	$<0.001^{s2/s4,\ s2/s6,\ s3/s6,\ s5/s6,\ s6/s7,}$
T4	9.59	**13.13**	19.49	12.8	8.6	11.19	11.71	13.49	$<0.001^{s1/s2,\ s2/s3,\ s2/s4,\ s2/s5,\ s2/s6,\ s2/s7,}$
T5	10.08	10.71	18.25	10.21	8.8	**13.62**	12.47	15.86	$<0.001^{s1/s2,\ s2/s3,\ s2/s4,\ s2/s6,\ s4/s7}$
T6	8.01	11.34	17.24	**18.18**	7.15	14.35	9.32	14.41	$<0.001^{s2/s4,\ s2/s6,\ s3/s4,\ s3/s6,\ s4/s5,}$
TF	7.66	12.12	17.24	9.65	10.75	**13.72**	12.62	16.22	$<0.001^{s2/s3,\ s2/s4,\ s3/s7,\ s4/s7}$

Table 3: Number of participants in Motivated (M) and Demotivated (D) states across dashboards and clusters. C1, C2, and C3 refer to Cluster 1, 2, 3, respectively.

Dashboard	M	D	M_C1	D_C1	M_C2	D_C2	M_C3	D_C3
A1	9	7	6	3	2	1	1	3
A2	7	3	4	1	3	0	0	2
A3	6	4	3	3	1	1	2	0
A4	7	0	4	0	1	0	2	0
A5	6	3	4	2	2	0	0	1
A6	2	2	0	1	1	1	1	0
AF	9	0	6	0	2	0	1	0
T1	**15**	2	6	0	5	1	4	1
T2	2	**11**	1	2	1	3	0	6
T3	5	5	1	4	1	1	3	0
T4	6	5	4	1	1	2	1	2
T5	4	6	2	3	2	2	0	1
T6	6	1	3	1	0	0	3	0
TF	5	4	1	2	2	1	2	1

Table 4: Top three most frequent comparison sequences of length three with A-B-A pattern along with their weight. Seq1, Seq2, and Seq3 indicate the top three most frequent sequences. Underlined are the most participant's identified LAD element (peers) they compared with the most.

Dashboard	Seq1/w	Seq2/w	Seq3/w
A1	s5-s6-s5/4.7	s5-s4-s5/4.4	s2-s1-s2/4.2
A2	s2-s3-s2/5.3	s2-s1-s2/4.1	s5-s4-s5/3.8
A3	s2-s7-s2/5.6	s5-s4-s5/5.3	s2-s3-s2/4.5
A4	s2-s1-s2/7.1	s2-s3-s2/4.4	s5-s6-s5/4.3
A5	s2-s1-s2/6.5	s5-s6-s5/5.0	s2-s7-s2/4.5
A6	s2-s1-s2/5.2	s2-s7-s2/4.6	s1-s2-s1/4.0
AF	s2-s1-s2/8.8	s5-s6-s5/7.6	s5-s4-s5/6.8
T1	s5-s6-s5/5.1	s2-s1-s2/4.6	s2-s7-s2/4.0
T2	s5-s6-s5/4.4	s2-s3-s2/4.2	s2-s1-s2/3.0
T3	s2-s1-s2/5.0	s5-s4-s5/4.0	s2-s3-s2/3.9
T4	s2-s3-s2/3.2	s2-s3-s2/3.1	s1-s7-s1/3.1
T5	s2-s7-s2/4.4	s2-s1-s2/4.0	s2-s3-s2/3.4
T6	s3-s7-s3/5.5	s2-s1-s2/4.6	s5-s4-s5/3.4
TF	s6-s5-s6/6.3	s2-s7-s2/6.3	s2-s5-s2/6.3

5 Discussion

5.1 Participants Sensemaking Outcomes

According to Table 1a, in dashboards A1 and A2, as well as in the full dashboard, the peer with the same ability was reported as the one with whom the participants compared themselves most. In A3 and A6, the peers with the highest ability had the highest comparison frequency reported by participants. The peer with the lowest ability only had the highest comparison rate in dashboard A5. In terms of ability level, it can be seen that in six out of seven dashboards, the participants reported the peer with either the highest or the same level of ability as the most compared-with peer. Moving to time-related characteristics as presented in Table 1b, the peer with the same time spent on the task was the most compared-with peer in dashboards T1 and T2. For the remaining time dashboards, participants compared themselves with peers at either the lowest or highest extreme with respect to the time spent on the task.

Regarding performance, participants reported that the peers with the same performance were the ones they compared themselves with the most in dashboards A3 and T3. The most notable characteristic among the highly compared peers was the highest performance, which appeared in seven dashboards, including A4-A6, T4-T6 (all dashboards with the same or lower grades), and the full dashboard. There were no notable comparisons with the peers with the lowest performance, demonstrating that the participants prefer to compare themselves more with peers who achieved better grades or have the same level of ability.

5.2 Affordances of Eyetracking Features for Understanding Participants' Sensemaking

By triangulating self-reported and eye-tracking derived gaze time in Tables 1a and 2, that in all ability dashboards, the reported highly compared-with peers had the highest gaze time (disregarding students themselves). Triangulating Tables 1b and 2, this observation is also valid in five out of seven dashboards in the time group. Therefore, we can conclude that the highest gazed element on the dashboards may indicate the element that plays the most important role for LAD viewers, a finding corroborated by Just & Carpenter [16].

Concerning the gaze time durations, one notable observation from ANOVAs and Tukey HSD tests reported in Table 2 is a significantly higher gaze duration of s7 on dashboards A1 and T1, which can be attributed to participants' sensemaking process when they are prompted with the time and ability dashboards for the first time.

By triangulating Tables 1a and 4, we observe that at least one most compared-with peer is present in the most frequent comparison sequences in the Ability group. Similarly, a triangulation of Tables 1b and 4 reveals that this observation also holds for six out of seven dashboards in the Time group. However, it should be taken into consideration that s2's high fixation duration across all dashboards, may to some extent, be attributed to the 'central fixation bias' [26], a tendency to fixate on the center of images displayed on monitors during first-time viewing, i.e., on AOI for peer s2.

Weight information for most frequent comparison sequences in Table 4 revealed that the weights of the full dashboards (AF and TF) are generally higher compared to other dashboards. This can be explained by the participants' higher cognitive load, as it takes more effort to make sense of newly introduced LAD elements in full dashboards (time spent in AF, ability level in TF).

It can be seen that dashboard T1 was the most motivating dashboard, reported by 15 participants, with only 2 reporting demotivation. This suggests the highly motivating characteristics of this dashboard (higher grade, higher time spent). On the other hand, T2 was pointed out by 11 participants as a demotivating dashboard, with only 2 participants deeming it motivating. The highest number of contradictory views were directed towards dashboard A1, reported by 9 participants as motivating and 7 participants as demotivating. Interestingly, dashboards A4 and AF were the ones in which no participants reported demotivation after viewing them. At the same time, these two dashboards were relatively motivating, with 9 and 7 motivated participants, respectively. Another notable point is that the full dashboard appeared to be highly motivating for the Ability group, with no demotivated participants. However, for the Time group, this dashboard was reported as demotivating by 4 participants and motivating by 5, which shows the priming effect for participants in the Ability group.

As stated in Section 4.3, we cannot confirm a significant connection between gaze duration portions and the participants' motivation due to the small sample sizes. We also examined the eye-tracking data to explore any potential connection between the participants' motivational state and their eye movement patterns, but no significant correlation was found.

5.3 Limitations

A small number of participants in this exploratory study limited the viability of statistical analyses, especially at the cluster level. Additionally, the participants were from a single program, further limiting generalization of our results.

6 Conclusions

In conclusion, in the present study, we explored how eye-tracking derived features can inform researchers about the students' sensemaking process while they view different elements of LADs, including grade, time spent, and ability. Our findings reveal that extracted eye-tracking features (gaze duration, eye movement pattern) closely match their cognitive process while making comparative evaluations.

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