Linking Dashboard Elements and Retrospective Outcome Emotions in Dashboard Feedback: A Transmodal Analysis

Tianyi Wang
Simon Fraser University
Burnaby, Canada
twa171@sfu.ca

Marek Hatala
Simon Fraser University
Burnaby, Canada
mhatala@sfu.ca

Arash Ahrar
Simon Fraser University
Burnaby, Canada
arash_ahrar@sfu.ca

Zhiqing Zheng
Simon Fraser University
Burnaby, Canada
zhiqing_zheng@sfu.ca

Abstract

Learning analytics dashboards (LADs) are widely used to present information about learners' outcomes. However, few studies have examined how specific LAD elements, particularly those involving varying degrees of social comparison, contribute to students' retrospective outcome emotions of pride, relief, disappointment, and shame. This study applies a transmodal analysis of eye-tracking data to identify viewing patterns of LAD elements critical to these emotions. Using data from 96 participants viewing dashboards that presented their assignment performance, we demonstrate how students' gaze focus differed between those who experienced different retrospective outcome emotions and those who did not. Our findings suggest directions for future research on developing personalized, emotion-aware learning environments.

CCS Concepts

• **Human-centered computing → Visualization**; • **Applied computing → Education**.

Keywords

achievement emotions, dashboards, eye-tracking, transmodal analysis

ACM Reference Format:
Tianyi Wang, Marek Hatala, Arash Ahrar, and Zhiqing Zheng. 2026. Linking Dashboard Elements and Retrospective Outcome Emotions in Dashboard Feedback: A Transmodal Analysis. In *LAK26: 16th International Learning Analytics and Knowledge Conference (LAK 2026), April 27–May 01, 2026, Bergen, Norway.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3785022.3785090

1 Introduction

Maintaining students' motivation, especially in the face of setbacks, is a persistent challenge in higher education. Learning Analytics Dashboards (LADs) aim to address this by visualizing learning and performance data (e.g., time on task, grades, peer comparisons) to promote awareness, reflection, and self-regulated learning [7, 10]. Increasingly embedded in digital learning environments, dashboards are widely regarded as tools to enhance student engagement. However, empirical findings remain mixed: while some studies report modest motivational benefits, others suggest that dashboards can elicit confusion, disengagement, or anxiety, particularly when students interpret the feedback in ways that conflict with their goals or prior beliefs [2, 21].

Recent work indicates that dashboards are not passive feedback tools but active psychological stimuli [1]. When students view a dashboard, particularly one showing performance comparisons or prior results, they often engage in a causal interpretation process: Why did I do well or poorly? What does this say about me? Such interpretations can evoke strong emotions such as pride, guilt, relief, or anxiety, which in turn shape students' motivation and subsequent engagement [1, 15]. This link between emotional response and motivation is central to foundational psychological frameworks such as Pekrun's Control-Value Theory [15]. These theories provide a robust foundation for understanding how students experience dashboards and why emotional and motivational responses may differ across learners.

In turn, students' emotional reactions to feedback have the potential to reveal the state of their goals and expectations. For example, if a student responds with disappointment to high grades or a strong ranking, this may indicate that their goals and expectations were set even higher [4]. Conversely, experiencing relief after mediocre results may reflect low expectations or recognition of limited effort. Although substantial effort has been devoted to detecting emotional states such as boredom, enjoyment, and confusion, relatively little work has focused on outcome emotions such as pride and disappointment in response to feedback (e.g., [26]), particularly in the context of dashboards (e.g., [1, 4]). Because facial detection of retrospective outcome emotions is constrained by the lack of labeled datasets, this study explores whether students' gaze on dashboard elements, captured through eye tracking, can be used to differentiate those who experience pride, relief, disappointment, and shame.

2 Background

2.1 Retrospective Outcome Emotions

Achievement emotions are emotions linked to achievement activities (e.g., studying) or outcomes (e.g., success or failure) [17]. According to Pekrun's three-dimensional taxonomy, they are characterized by three elements: valence, arousal, and object focus

LAK 2026, Bergen, Norway

ACM ISBN 979-8-4007-2066-6/26/04
https://doi.org/10.1145/3785022.3785090

[16]. Valence distinguishes between positive and negative emotions, while arousal separates activating from deactivating emotions. Object focus links emotions to the achievement context, categorizing them into activity emotions, prospective outcome emotions, and retrospective outcome emotions [16]. Within outcome emotions, prospective emotions such as joy and hopelessness are tied to anticipated results, whereas retrospective emotions such as pride and shame are associated with perceived past success or failure [17].

Retrospective outcome emotions play a crucial role in learners' motivation. Different emotions such as pride, relief, disappointment, and shame have distinct effects on students' learning [12]. Positive activating emotions, such as pride, can enhance motivation, whereas negative deactivating emotions, such as disappointment, can reduce it [15]. Activating retrospective emotions, including pride and shame, are tied to perceptions of self-responsibility. In contrast, deactivating retrospective emotions, such as relief and disappointment, arise when outcomes deviate from expectations: relief occurs when success follows anticipated failure, and disappointment occurs when failure follows expected success [16].

According to Pekrun's control-value theory (CVT) [15], the antecedents of achievement emotions include both environmental factors (such as students' goal structures, expectations, and feedback) and students' appraisals of control and value (including expectancies and attributions). CVT further posits that specific emotions arise from particular combinations of these antecedents. Thus, it may be possible to infer aspects of students' goals and expectancies from the emotions observed in response to specific feedback, positioning emotion detection as an important conduit for developing personalized systems.

2.2 Dashboard Research at Element Level

A central area of focus within learning analytics is the development of dashboards, designed to support students' self-regulated learning by enhancing awareness, reflection, motivation, and behavior [25]. The configuration of dashboard elements, particularly those involving social comparison, has become a critical design consideration due to their emotional and motivational implications [1, 2]. Yet most research has examined the impact of dashboards as a whole, typically comparing outcomes in dashboard versus non-dashboard conditions [10]. Only a few of studies have analyzed dashboards at the element level, and these have typically employed qualitative approaches (e.g., [1, 4, 9]).

Eye-tracking systems capture data such as gaze points, fixation durations, and pupil size variations [18], offering an opportunity to study dashboards at the element level. Although eye-tracking is a well-established research method, only a few studies used it to study how students utilize LADs. For example, [8] found that students who spent more time viewing the textual components of graphs in LADs demonstrated higher comprehension than those who focused primarily on graphical components. Similarly, [3] showed that eye-tracking features are strong indicators of students' social comparison tendencies and provide valuable insights into their sensemaking processes. Our study extends this work by categorizing dashboard elements according to their information content and using eye-tracking to analyze the sequences in which students attend to these elements during sensemaking.

2.3 Research Question

The elements in the dashboard that students focus on can reveal how they interpret their own results in relation to their goals and expectations, as framed by the other information presented. Since gaze is indicative of cognition [22], gaze patterns can reflect hidden internal states such as goals, expectations, and motivation, which are critical for informing pedagogical interventions [26] or automated personalization [5]. According to goal-setting theory [13], the alignment or misalignment with students' goals gives rise to emotional responses. Our research question is: Do students who experience retrospective outcome emotions focus on different LAD elements than those who do not?

3 Methods

3.1 Study Context

We conducted a laboratory study to examine how students' achievement emotions are associated with specific dashboard elements. 96 undergraduates enrolled in first- and second-year programming courses at a post-secondary institution in North America participated in the study. The majority of participants were aged 18–24 (n = 91), with five aged 25–30. All reported familiarity with common graphs. Gender distribution was 53 women, 41 men, 1 non-binary, and 1 undisclosed. Each participant viewed their assignment grade for the first time through the dashboard (see Fig. 1), presented in a lab setting. The dashboard design, selected in a previous qualitative study with 39 participants that examined thirteen alternatives [1], displayed each participant's own grade and time spent on the assignment in the top section, and six closest peers with higher grades and time spent in the lower section. Upward comparison on both grades and time spent was the most motivational for students, whereas downward, horizontal, or mixed comparisons often elicited mixed or demotivating reactions. All grades were collected directly from the LMS, and time spent was self-reported at the time of assignment submission.

During dashboard viewing, eye movements were tracked to identify which elements students focused on (i.e., Areas of Interest, AOIs). AOIs were defined as the participant's own performance element and the six peer elements, shown as rectangles in Figure 1. We have used screen-mounted Gazepoint GP3HD V2 (accuracy 0.5–1.0°, 60 Hz, 60cm distance), following a 9-point calibration.

After viewing the dashboard, students completed the section of the Achievement Emotion Questionnaire (AEQ-R, [16]) measuring retrospective outcome emotions: pride (6 items, e.g., "To think about my success makes me feel proud."), disappointment (4, e.g., "I am disappointed that I did not perform well."), relief (5, e.g., "I feel relieved when I learn I have not done poorly."), and shame (6, e.g., "I feel ashamed because I realize that I lack ability."), each rated on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). For analysis, following the approach adopted by [11], a mean value of 3.5 was used as threshold to dichotomize Likert-scale responses, classifying them as either experiencing or not experiencing the given emotion (e.g., proud vs. not proud). This approach effectively distinguishes between neutral and affirmative positions and aligns with preferences for modeling interpretability in educational contexts. The counts of each emotion, students' grades, and emotion co-occurrences are presented in Table 1.

Figure 1: Learning analytics dashboard showing the student's grade and time spent on Assignment 3 alongside six peers, with indicated Areas of Interest (AOIs).

Table 1: Retrospective outcome emotions counts and grades median and interquartile ranges for students reporting emotion (Yes) and not (No). Emotion co-occurrence counts.

	Present: Yes		Present: No		Emotion Co-occurrence			
Emotion	n	Grades Mdn (IQR)	n	Grades Mdn (IQR)	Disap.	Relief	Pride	Shame
Disappointment	25	73 (54 - 73)	71	94 (82 - 100)	25	12	4	17
Relief	71	92 (82 - 100)	25	68 (48 - 88)	12	72	49	16
Pride	51	98 (87 - 100)	45	79 (55 - 95)	4	49	52	7
Shame	24	80 (63 - 91)	72	91 (82 - 100)	17	16	7	24

3.2 Coding Dashboard Elements Values

Because the six peers displayed were selected as the nearest peers with higher grades and greater time spent compared to each participant, the peers shown in each dashboard differed. We calculated the relative differences in grade and time between the student and the displayed peers. To facilitate analysis, we preprocessed the AOI data and grouped these differences into discrete levels. Based on the distributions (Figure 2), grade differences were coded as Grade Low (GL, 0–5), Grade Middle (GM, >5–15), and Grade High (GH, >15). Time differences were categorized using the same thresholds: Time Low (TL, 0–5), Time Middle (TM, >5–15), and Time High (TH, >15).

In the dashboard, each peer performance AOI was assigned one of nine grade–time difference labels: GLTL, GLTM, GLTH, GMTL, GMTM, GMTH, GHTL, GHTM, or GHTH. The top section, showing the participant's own grade and time, was labeled as Self. For example, in Figure 1, the Self area displays the student's grade (61%) and time spent (6h). Peer Student 4 has a grade of 74% and a time of 9h. The grade difference of 13 falls into the Grade Middle (GM) category, while the time difference of 3h falls into the Time Low (TL) category. Thus, the AOI for Peer Student 4 is labeled GMTL.

3.3 Model Construction using Transmodal Analysis

To analyze gaze patterns in dashboards, Ahrar et al. [3] summed fixation times on dashboard elements and counted saccades, that is, movements between elements, using an A–B–A comparison pattern. This approach is limited to identifying patterns involving only one or two elements. As students revisit elements, they tend to fixate on those that help them make sense of their own information. During fixation, they also hold in working memory several of the

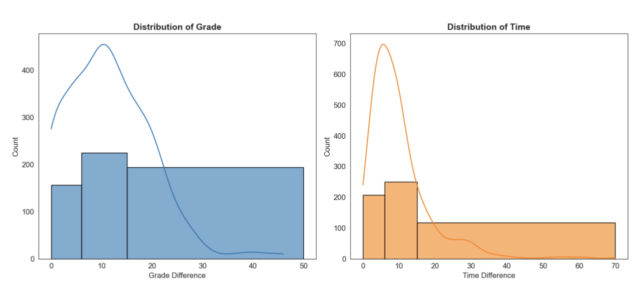


Figure 2: Distribution of Grade and Time Differences

most recently viewed elements [24]. Prior work further suggests that people retain stronger memory traces for more salient events [6], meaning that certain elements, such as one's own performance or peers with sharply contrasting results, may continue to influence sensemaking for a longer period.

To account for differences in the temporal influence of elements during viewing, we used Transmodal Analysis (TMA) [20], which models how events affect subsequent events over time. We assumed that elements with high grade differences, particularly those exceeding time differences, as well as the Self element, exert a longer cognitive influence during sensemaking. Accordingly, we specified different temporal windows for TMA's influence functions (TIFs) for fixations on AOIs with different labels. TIFs gradually reduce the influence of earlier elements within predefined windows. To establish TIF thresholds, we used a fixed-window algorithm to estimate elements viewed per second; on average, participants viewed one element per second. Given evidence that refixations typically occur after fixations on up to two other objects [28], we set the TIF windows to 7 seconds for high-influence elements and 3 seconds for others, reflecting both empirical viewing behavior and known refixation dynamics. We then applied the TMA package [14] to aggregate gaze behavior across LAD elements.

3.4 Analyzing Gaze Behaviours using Ordered Network Analysis

To address our research question, we compared graphical representations of gaze transitions between labeled AOIs for students who experienced a specific emotion after viewing the dashboard and those who did not. Epistemic Network Analysis (ENA) is a method for identifying and quantifying connections among coded elements and representing them in dynamic network models [19]. We applied a related method, Ordered Network Analysis (ONA) [23], which models how events unfold in sequence during processes such as collaborative learning or dashboard viewing. ONA captures both the temporal order of connections between constructs, here, AOI labels such as GLTL, GLTM, and others, as well as their self-transitions.

After aggregating gaze behaviours from all participants using TMA, we visualized two ONAs for each retrospective outcome emotion: one for participants who experienced the emotion and one for those who did not. We analyzed each emotion separately. To examine how emotion and non-emotion groups focused on different dashboard elements, each ONA represented ordered connections among ten AOI codes: GLTL, GLTM, GLTH, GMTL, GMTM, GMTH, GHTL, GHTM, GHTH, and Self. To compare viewing behaviours, we created differential graphs between the groups and interpretted them.

4 Results

Figure 3 presents the difference models comparing participants who experienced each retrospective outcome emotion. In each chart, low grade difference elements (GLTL, GLTM, GLTH) cluster toward the bottom left, high grade difference elements (GHTL, GHTM, GHTH) appear at the bottom right, and medium grade difference elements (GMTL, GMTM, GMTH) are located in the top right. Below, we describe each graph in detail, focusing on the transitions that show the strongest differences between the two groups.

Disappointment. Fig. 3a compares participants who experienced disappointment with those who did not. The location of the small blue mean square indicates that non-disappointed participants tended to focus more on elements showing lower grade differences (GL), forming more connections among them. They exhibited frequent transitions between GLTL↔Self, GLTM↔Self, GLTL↔GLTM, and GMTM↔GMTH, including self-transitions of GLTL, GLTM, and GMTH. Connections from GLTL→GLTH, GLTM→GLTH, GLTL→GMTM, and GLTM→GMTM also appeared stronger.

In contrast, disappointed participants (red) focused more on GH elements as well as the medium-grade, low-time element (GMTL). They exhibited strong transitions between GMTL↔Self, GMTL↔GHTM, GMTL↔GMTM, and GHTM↔Self, along with moderately strong transitions between GMTL and GLTL/GLTM and between GMTM and GHTL. They also showed self-transitions of GMTL and GHTM. Among all nodes, GMTL and Self had the largest outer circle radius, indicating they were the most common response points to other codes.

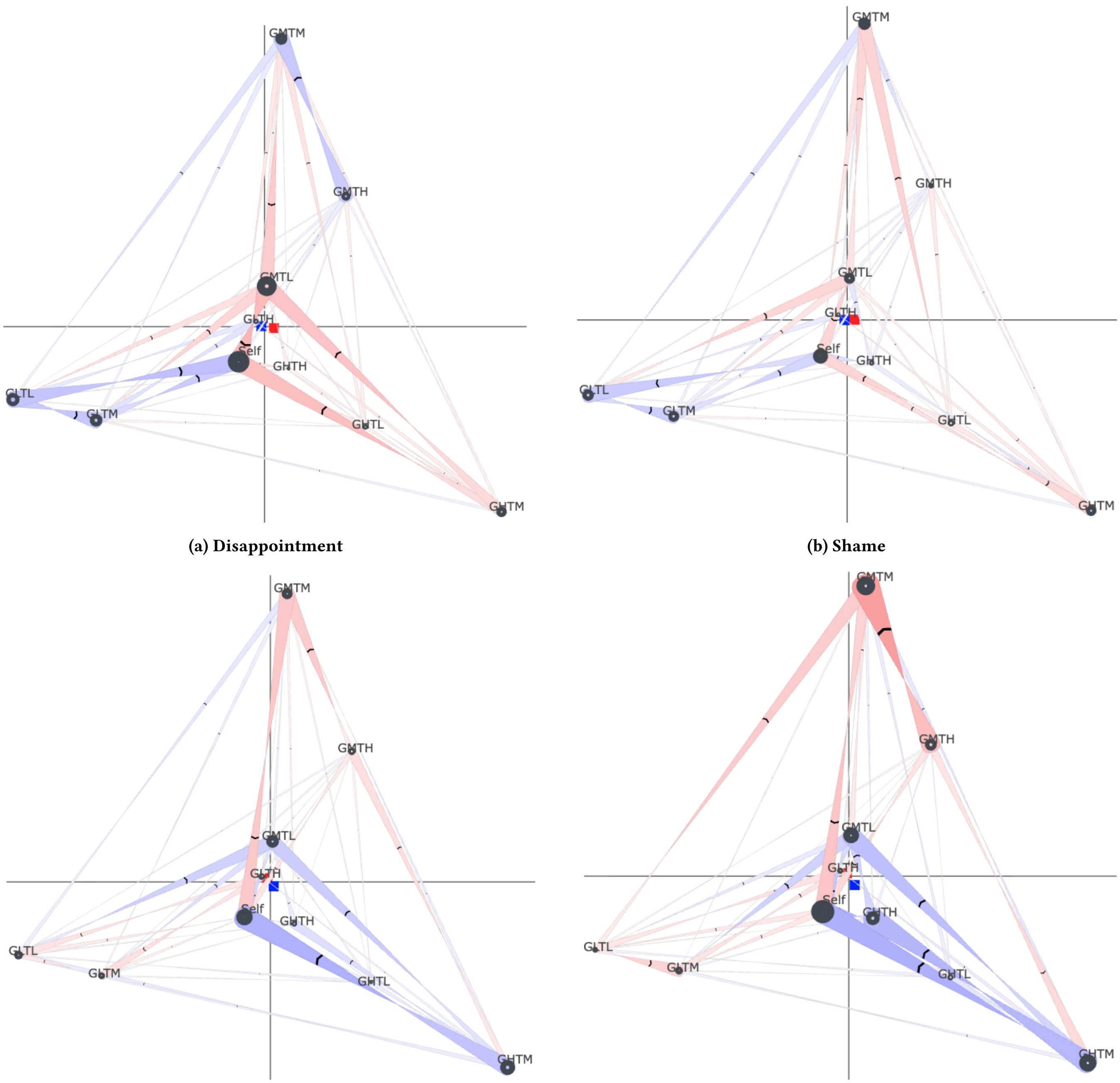
Shame. Fig. 3b compares participants who experienced shame with those who did not. Non-shame participants tended to focus more on elements with low grade differences (GL). They showed frequent transitions between GLTL↔Self, GLTM↔Self, GLTL↔GLTM, GMTM↔GMTH, GLTL↔GMTM, and GMTM↔GLTM, including self-transitions of GLTL and GLTM. Connections from Self→GLTL, GLTM→Self, GLTL→GLTM, GLTL→GMTM, and GMTH→GMTM appeared stronger.

In contrast, participants who experienced shame (red) were more likely to focus on GH elements (GHTL, GHTM) as well as GMTL. They showed strong transitions between GMTM↔GHTL, GMTL↔Self, GMTL↔GMTM, and GLTL↔GMTL, along with moderately strong transitions between GHTM↔Self, GMTL↔GLTM, GMTM↔Self, GHTL↔Self, GMTH↔GHTL, GHTM↔GHTL, and GMTH↔GHTM. They also exhibited strong self-transitions of GHTL, GMTL, and GHTM.

Pride. Figure 3.c compares participants who experienced pride with those who did not. Pride participants (red) tended to focus more on elements with low grade differences (GL) and on medium grade difference elements (GM) paired with higher time differences (TM, TH). They showed strong transitions between GMTM↔Self, GMTM↔GMTH, and GMTH↔GHTM, including self-transitions of GLTL, GMTM, and GMTH. Connections from GMTM→Self, GMTH→GMTM, and GHTM→GMTH appeared stronger.

In contrast, non-pride participants were more likely to focus on high grade difference elements (GH) as well as on element with medium grade and low time differences (GMTL). They exhibited strong transitions between GMTL↔GLTL, GMTL↔GHTM, and GHTM↔Self. They also showed strong self-transitions of GMTL, GHTH, and GHTM.

Relief. Figure 3.d compares participants who experienced relief with those who did not. The patterns for relief were similar to those observed for pride. However, when participants experienced relief, stronger connections emerged between GMTM and GMTH, as well as between GLTL and GMTM. In contrast, participants who did not experience relief showed a greater influence of GHTH compared to the non-pride condition.



(a) Disappointment

(b) Shame

(c) Pride

(d) Relief

Figure 3: ONA difference models for retrospective outcome emotions. Red connections are more frequent for participants who experienced the emotion, and blue connections for those who did not. The squares represent the respective network centroids. Larger circles represent more frequent transitions from other nodes within the temporal window. Bi-directional line weights indicate the strength of connections in each direction, with the stronger one marked by a chevron.

5 Discussion and Future Research

In this study, the use of TMA enabled the mapping and analysis of gaze fixations on dashboard elements, allowing us to identify differences in areas of focus between students who experienced retrospective outcome emotions and those who did not. Understanding how students' attention to dashboard elements varies during dashboard viewing opens a path toward predicting their emotional responses to feedback and, potentially, linking these reactions to the antecedents of emotions, such as students' goals, expectations, and aptitudes, as postulated by theories of motivation [15, 27]. The methodological contribution of this study is demonstrated through the effective use of TMA, which addresses the inherent challenges of analyzing gaze behaviors during dashboard viewing.

Presenting students with their actual assignment grades in the context of an important course provides strong ecological validity to our results. Students had invested effort in the assignments that accounted for a significant portion of their grades and formed expectations about their outcomes. They saw their results for the first time in the dashboard, which ensured a genuine emotional response, despite being presented with the dashboard in the lab setting. However, because achievement emotions have multiple antecedents [15, 27], students with similar outcomes may have attended to different elements of the dashboard and reacted in different ways. In this exploratory study, our goal was to examine whether students who reported the same emotional reactions tended to focus on the same types of dashboard elements. Investigating which unobserved factors, such as goals and expectations, drive these reactions remains an important direction for future research.

In the context of a challenging programming course, many students experienced positive emotions of pride and relief, while fewer students reported negative emotions of disappointment and shame, again despite a wide range of grades. This confirms that emotional reactions to feedback are strongly influenced by their antecedents, as discussed above. Consistent with expectations [15], many students experienced multiple emotions, most often two positive or two negative. However, we also observed mixed emotional reactions. Future research should investigate the extent to which these mixed responses are driven by students' internal antecedents as opposed to the specific design and content of the dashboard.

The use of ONA, with its fixed projection space, allowed us to effectively compare gaze patterns across emotions and between groups who experienced them and those who did not. The two positive emotions (pride and relief) and the two negative emotions (disappointment and shame) showed broadly opposite patterns of focus on dashboard elements, with nuances in the strength of gaze directed to different element types. For each emotion, we found a clear distinction between the elements students focused on when they experienced the emotion and when they did not.

Participants who focused on elements with low grade difference and compared them with their grade generally did not feel disappointed, since peers performed similarly but spent more time. In contrast, those who attended to elements showing high grade differences experienced disappointment more often. An interesting pattern of comparisons also emerged between peer elements: non-disappointed students focused on peers with low and medium grade differences paired with higher time differences, while disappointed students focused on peers with medium or high grade differences combined with low time differences.

Given the sizable group of students who experienced both shame and disappointment, those with shame focused on similar elements, although the connections were not as strong as for disappointment. Overall, the results suggest that shame arises mainly when participants focus on peers who show greater grade differences than time differences. Unlike disappointment, however, GHTL carries more weight in shame. We have observed that when the grade difference is much larger than the time difference, participants are more likely to feel shame.

Transitions between elements with low grade differences and Self showed only weak connections with pride or relief (these two emotions also frequently co-occurred). In contrast, elements with medium grade differences, particularly GMTM and GMTH, were more strongly associated with them. This suggests that participants were more likely to experience pride and relief when they focused on peers who performed moderately better but also invested a moderately or significantly higher amount of time. However, when peers performed moderately better but invested only slightly more time (GMTL), or when peers had high grade differences, participants were less likely to feel pride or relief.

This study confirmed that gaze patterns, as analyzed using the TMA approach, reveal clear distinctions between students who experienced different retrospective outcome emotions. Although the course context was specific, the processes underlying emotional reactions are largely generic, driven mainly by students' internal factors and only partially influenced by the achievement context, such as task difficulty [15]. At the same time, the generalizability of our results is limited by the specific dashboard design, including its graphical elements and the arrangement of peer AOIs. Replicating the study with different dashboard layouts and element types is needed to confirm the utility of gaze patterns for uncovering the emotional impact of dashboard feedback. Finally, several threshold parameters were selected during the analysis, both in TMA and in binarizing questionnaire responses, and choosing different thresholds may shift the results to some extent.

6 Conclusion

This study explored how students' gaze focus differs depending on whether they experienced different retrospective outcome emotions, suggesting possibilities for future research on developing personalized, emotion-aware learning environments. In particular, tailoring dashboard elements to students' performance levels may help address their diverse motivational needs. Our findings demonstrate the feasibility of applying TMA to dashboard gaze data and highlight the value of analyzing dashboards at the element level.

References

[1] Kimia Aghaei. 2023. *Investigating students' emotional and motivational responses to Dashboards with varying social comparison groups.* Msc Thesis. https://summit.sfu.ca/item/36716

[2] Kimia Aghaei, Marek Hatala, and Alireza Mogharrab. 2023. How Students' Emotion and Motivation Changes after Viewing Dashboards with Varied Social Comparison Group: A Qualitative Study. In *The 13th Int. Conf. on Learning Analytics & Knowledge.* 663–669. doi:10.1145/3576050.3576107

[3] Arash Ahrar, Mohammadreza Doroodian, and Marek Hatala. 2025. Exploring Eye-tracking Features to Understand Students' Sensemaking of Learning Analytics Dashboards. In *Proceedings of the 15th International Learning Analytics and Knowledge Conference.* 931–937.

[4] Liz Bennett and Sue Folley. 2021. Students' Emotional Reactions to Social Comparison via a Learner Dashboard. In *Visualizations and Dashboards for Learning Analytics*, M. Sahin and D. Ifenthaler (Eds.). Springer, Cham, 233–249. doi:10.1007/978-3-030-81222-5_11

[5] Matthew L. Bernacki, Meghan J. Greene, and Nikki G. Lobczowski. 2021. A Systematic Review of Research on Personalized Learning: Personalized by Whom, to What, How, and for What Purpose(s)? *Educational Psychology Review* 33 (2021), 1675–1715. doi:10.1007/s10648-021-09615-8

[6] Reto Bisaz, Alessio Travaglia, and Cristina M Alberini. 2014. The neurobiological bases of memory formation: from physiological conditions to psychopathology.

Psychopathology 47, 6 (2014), 347–356.

[7] Robert Bodily and Katrien Verbert. 2017. Trends and issues in student-facing learning analytics reporting systems research. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference (LAK '17)*. Association for Computing Machinery, New York, NY, USA, 309–318. doi:10.1145/3027385.3027403

[8] Il-Hyun Jo, Kunhee Ha, and Yeonjeong Park. 2015. Measuring Information Perception in Learning Analytics Dashboard: Use of Eye-Tracking System. *The Journal of Korean Association for Educational Information and Media* 21, 3 (Sept. 2015), 441–469. doi:10.15833/KAFEIAM.21.3.441

[9] Paul Joseph-Richard, James Uhomoibhi, and Andrew Jaffrey. 2021. Predictive learning analytics and the creation of emotionally adaptive learning environments in higher education institutions: a study of students' affect responses. *International Journal of Information and Learning Technology* 38, 2 (2021), 243–257. doi:10.1108/IJILT-05-2020-0077

[10] Rogers Kaliisa, Kamila Misiejuk, Sonsoles López-Pernas, Mohammad Khalil, and Mohammed Saqr. 2024. Have Learning Analytics Dashboards Lived Up to the Hype? A Systematic Review of Impact on Students' Achievement, Motivation, Participation and Attitude. In *Proceedings of the 14th Learning Analytics and Knowledge Conference (LAK '24)*. Association for Computing Machinery, New York, NY, USA, 295–304. doi:10.1145/3636555.3636884

[11] James R. Lindner and Nicholas J. Lindner. 2024. Interpreting Likert-type Scales, Summated Scales, Unidimensional Scales, and Attitudinal Scales: I neither Agree nor Disagree, Likert or Not. *Advancements in Agricultural Development* 5, 2 (2024), 152–163.

[12] Bowen Liu, Wanli Xing, Yifang Zeng, and Yonghe Wu. 2021. Quantifying the Influence of Achievement Emotions for Student Learning in MOOCs. *Journal of Educational Computing Research* 59, 3 (June 2021), 429–452. doi:10.1177/0735633120967318

[13] Edwin A Locke and Gary P Latham. 2002. Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American psychologist* 57, 9 (2002), 705.

[14] Cody L Marquart, Muhammad Hasnat Ashiq, and David Williamson Shaffer. 2025. *tma: Transmodal Analysis (TMA)*. https://CRAN.R-project.org/package=tma R package version 0.3.1.

[15] Reinhard Pekrun. 2006. The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational psychology review* 18, 4 (2006), 315–341.

[16] Reinhard Pekrun, Herbert W. Marsh, Andrew J. Elliot, Kristina Stockinger, Raymond P. Perry, Elisabeth Vogl, Thomas Goetz, Wijnand A. P. van Tilburg, Oliver Lüdtke, and Walter P. Vispoel. 2023. A three-dimensional taxonomy of achievement emotions. *Journal of Personality and Social Psychology* 124, 1 (2023), 145–178. doi:10.1037/pspp0000448

[17] Reinhard Pekrun and Elizabeth J Stephens. 2010. Achievement emotions: A control-value approach. *Social and Personality Psychology Compass* 4, 4 (2010), 238–255.

[18] Jonathan L. Rosch and Jennifer J. Vogel-Walcutt. 2013. A review of eye-tracking applications as tools for training. *Cognition, Technology & Work* 15, 3 (Aug. 2013), 313–327. doi:10.1007/s10111-012-0234-7

[19] David Williamson Shaffer, Wesley Collier, and A. R. Ruis. 2016. A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data. *Journal of Learning Analytics* 3, 3 (Dec. 2016), 9–45. doi:10.18608/jla.2016.33.3

[20] David Williamson Shaffer, Yeyu Wang, and Andrew Ruis. 2025. Transmodal Analysis. *Journal of Learning Analytics* 12, 1 (Jan. 2025), 271–292. doi:10.18608/jla.2025.8423

[21] Sanam Shirazi Beheshitha, Marek Hatala, Dragan Gasevic, and Srecko Joksimovic. 2016. The Role of Achievement Goal Orientations When Studying Effect of Learning Analytics Visualizations. In *Proc. of the Sixth Int. Conference on Learning Analytics And Knowledge - LAK '16*. 54–63. doi:10.1145/2883851.2883904

[22] Miriam Spering. 2022. Eye Movements as a Window into Decision-Making. *Annual review of vision science* 8 (2022), 427–448. doi:10.1146/annurev-vision-100720-125029

[23] Yuanru Tan, Andrew R. Ruis, Cody Marquart, Zhiqiang Cai, Mariah A. Knowles, and David Williamson Shaffer. 2023. Ordered Network Analysis. In *Advances in Quantitative Ethnography*, Crina Damşa and Amanda Barany (Eds.). Springer Nature Switzerland, Cham, 101–116. doi:10.1007/978-3-031-31726-2_8

[24] Stefan Van der Stigchel and Andrew Hollingworth. 2018. Visuospatial working memory as a fundamental component of the eye movement system. *Current Directions in Psychological Science* 27, 2 (2018), 136–143.

[25] Katrien Verbert, Erik Duval, Joris Klerkx, Sten Govaerts, and José Luis Santos. 2013. Learning Analytics Dashboard Applications. *American Behavioral Scientist* 57, 10 (2013), 1500–1509. https://journals.sagepub.com/doi/full/10.1177/0002764213479363

[26] Joshua Weidlich, Aron Fink, Ioana Jivet, Jane Yau, Tornike Giorgashvili, Hendrik Drachsler, and Andreas Frey. 2024. Emotional and motivational effects of automated and personalized formative feedback: The role of reference frames. *Journal of Computer Assisted Learning* (2024), 1–18. doi:10.1111/jcal.13024

[27] Bernard Weiner. 1985. An attributional theory of achievement motivation and emotion. *Psychological review* 92, 4 (1985), 548.

[28] Gregory J Zelinsky, Lester C Loschky, and Christopher A Dickinson. 2011. Do object refixations during scene viewing indicate rehearsal in visual working memory? *Memory & Cognition* 39, 4 (2011), 600–613.