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Associations between Students' Standing Seen in Learning Analytics Dashboards and Their Following Learning Behaviours: A Study of Three Reference Frames

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Abstract

An essential part of making dashboards more effective in motivating students and leading to desirable behavioural change is knowing what information to communicate to the student and how to frame and present it. Most of the research studying dashboards' impact on learning analyzes learning indicators of students as a group. Understanding how a student's learning unfolds after viewing the dashboard is necessary for personalized dashboard selection and its content. In the context of the discussion activity, we analyzed 28,290 actions of 896 students after they saw their learning status on the dashboards, which were integrated into 21 discussions in 11 courses. We provide a comparative perspective on three dashboard types: the class average, the leaderboard, and message-quality dashboards. Our results indicate that students' behaviours after viewing three dashboards were associated with their displayed standing in the discussion: views showing the student's status below the frame of reference were associated with a higher likelihood of posting, and views of the student outperforming the norm with diminished further posting, although demonstrating higher discussion engagement. We reiterate a need to understand the impact of dashboard states on students' behaviour, creating a foundation for a personalized selection of dashboard views based on individual students' standing.

Notes for Practice

- Students' standing shown in the dashboard is associated with the learning actions that followed.
- The observed actions of students after dashboard views varied based on a combination of dashboard type and the standing of the students.
- Personalization algorithms should consider relationships between students' status displayed on the dashboards and desirable learning behaviours.

Keywords

Student-facing dashboards, class average, leaderboard, learning behaviour, asynchronous online discussions.

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1. Introduction

Student-facing learning analytics dashboards (LADs) are one of the main outcomes of research in learning analytics aimed at informing students about their learning. Systematic studies mapping LAD research until 2018 (Bodily & Verbert, 2017a; Schwendimann et al., 2017; Jivet et al., 2018; Matcha et al., 2019) identified main gaps and recommended focusing on perceived and actual effects on student learning and outcomes, executing random controlled trials or quasi-experimental studies, examining student perceptions and perceived effects on student behaviour and achievement, and improving quality of reporting. Bodily and Verbert (2017b)'s review of 94 papers on LADs and other reporting systems found that while 30 articles focused on students' perceptions of usability and usefulness, only 15 articles evaluated the actual effect on student behaviour and 14 on student achievement, most of them using small sample sizes and descriptive statistics and having few significant results. Bodily and Verbert (2017b) concluded that "more research is needed on the actual effects of these reporting systems [LADs] on student behavior, student achievement, and student skills" (p. 314). Susnjak and colleagues (2022)'s analysis of 17 papers from

2018 to 2021 found that most LADs presented descriptive information, expecting students to reflect on it and change their learning behaviour. Most LAD evaluations focused on usability using qualitative approaches, such as surveys and interviews, within the pilot study context; only one quarter reported positive effects on student outcomes. This study confirmed prior observations of the limited evidence of dashboard effectiveness (Ferguson & Clow, 2017; Bodily & Verbert, 2017b). The most recent systematic review of LAD research (Kaliisa et al., 2024) focused on 38 studies with quantitative results, concluding that LAD impacts on achievement varied vastly, with little evidence of student performance improvement. These findings were further complicated by methodological issues, such as combining LADs with other (confounding) interventions, using a non-controlled design, with a prevalent comparison of LAD users against non-users, and not considering the intensity of dashboard use for the users. Kaliisa and colleagues (2024) concluded that applying different dashboard designs and learning activities may have different outcome impacts. To avoid the limitations of traditional evaluation methods, they proposed to "identify students' profiles of usage of LADs and to analyze how they are used within the learning process" (p. 303).

The above studies point to ongoing challenges in this relatively young field. Although some studies showed positive impacts on learning outcomes, more focus is needed to understand connections between patterns of use and learning behaviours and outcomes. This study aims to contribute to this effort by understanding the profiles of LAD usage (views) and how these views relate to the learning behaviour that follows. Specifically, we analyze students' behaviour immediately after viewing a dashboard. As student behaviours in larger contexts are influenced by a multitude of factors, we focused our study of LADs on the context of a single learning activity, asynchronous online discussions (AODs), with clearly measurable behaviours within the learning process. This study analyzed three different kinds of dashboards within the same activity, which allowed us to compare their varied associations with students' learning behaviours. By understanding how different LAD states viewed by a student and their behaviour relate, we point to personalizing LADs for individual students in concrete situations.

1.1 Measuring Students' Response to Dashboards

Students' response to dashboards can be measured in various ways, from an interpretation of their standing in the course when shown the dashboard by researchers (e.g., Corrin & de Barba, 2014) or advising staff (e.g., Lonn et al., 2015), differentiating dashboard and non-dashboard conditions without accounting for intensity of dashboard use (e.g., Davis et al., 2017), counting students' views of the dashboard and relating them to some achievement and their dashboard perception (e.g., Matz et al., 2021; Zamecnik et al., 2022), relating students' patterns of dashboard use to their self-regulatory behaviours (e.g., Kia et al., 2020), qualitatively evaluating students' interpretation of what they see in the dashboard and how they intend to change their learning behaviour (e.g., A. Wise et al., 2014; J. P. L. Tan et al., 2016; Han et al., 2021), relating some of the students' outcomes to their level of activity (e.g., Brusilovsky et al., 2016), students' aptitudes (e.g., achievement goal orientation; Shirazi Beheshitha et al., 2016), motivation (e.g., Bai et al., 2021; Balci et al., 2022), attribution to effort or ability (e.g., Aghaei et al., 2023), or other personal characteristic such as culture and individualism (e.g., Davis et al., 2017). Such a variety makes it difficult to generalize LADs' learning impact.

Trace-based approaches to capturing students' engagements with LADs are the most prevalent; they are often limited to counts of dashboard use over a studied period. However, such descriptive measures remove the dashboard views from the learning process as it unfolds (Sedrakyan et al., 2020). Further, the methods of analyzing the dashboard's influence on the learning process varied. As critiqued by Kaliisa and colleagues (2024), several studies compare LAD users against non-users, pitching more engaged students against disengaged ones. Some researchers differentiated their analyses based on "strong" and "weak" students, e.g., using GPA (Li et al., 2022), or how they placed on the leaderboard (Bai et al., 2021), using it as a proxy for what students *might* have seen on the LAD. In contrast, some researchers focused closely on LAD content or students' actions after viewing the LAD. For example, Teasley (2017) examined how students' prior academic performance and what the dashboard showed affected how they reacted to the information displayed. However, Teasley did not analyze students' actions after viewing the dashboard. This was done by Siadaty and colleagues (2015), who mapped learners' actions after viewing different types of dashboards using data mining, process mining, and social network analysis but did not connect them to the actual content of the dashboard at the time of viewing. In a few studies, researchers connected the views and following actions. A recent study by Li and colleagues (2022) presented students with the amount of time spent on homework in the first three weeks of the course by students with As, with Bs, and with Cs and lower in the prerequisite course. The LAD's effect, as measured by the time spent on homework in the following two weeks, differed based on students' performance and showed a significant increase against control for the low-performing group.

To summarize, cumulative measures across the groups of students or the final course outcomes were used most often to understand the LADs' impact on student learning, while studies connecting LAD-viewed content with behaviours are scarce. In this study, first, we aimed to deepen our understanding of the types of learning behaviours students exhibit directly *after* viewing a dashboard. By focusing on a graded small-group online discussion with clearly defined behaviours of reading, posting, and monitoring (A. F. Wise et al., 2013), we could analyze students' behaviours immediately after viewing the dashboard regarding these behaviours and how students integrated the LAD views with the discussion participation process.

1.2 Understanding the Impact of Dashboard Content

Most studies treat the presence of the dashboard, without considering its content, as one of the experimental conditions (Kaliisa et al., 2024). A few studies strive to understand the impact of viewing *particular* LAD information on students' motivation and subsequent learning actions. For this purpose, researchers carefully considered the LAD content that a student sees, including the student's performance and that of displayed (pre-selected) peers. Günther (2021) applied social comparison (see below) and social norms theory (Berkowitz, 2005) to design a LAD showing students' study time in the previous week compared with an average student and the most active students. Although the LAD did not lead to significantly longer learning time, the treatment group learned continuously while the control group crammed their learning toward the semester's end, a behaviour consistent with that of inactive and highly active students in the pre-experiment baseline. However, this study did not analyze the dashboard impact based on which view students saw, i.e., "Below Average," "Good," or "Great."

Fleur and colleagues (2020) designed a dashboard in which a student's average grade was shown with a carefully selected subgroup of nine peers: six with higher average grades and three with lower. The treatment group outperformed the control for formative assessments and the final grade. The extrinsic motivation increased for the treatment group while it dropped for the control; the intrinsic motivation decreased at the same rate for both groups.

Russell and colleagues (2020) showed students their quiz and homework scores compared to the class average, the possible maximum, and the projected final grade trajectory and explicitly worded final grade estimate. For moderate- and high-risk groups, as determined after the first midterm, the dashboard users showed higher scores on the second midterm; the risk of withdrawal was slightly lower for the high-risk group, and it was significantly lower for the moderate-risk group. The number of dashboard views was positively associated with achieving a C^{-} or better grade for the high-risk group.

Aguilar (2022) manipulated the class average when studying how viewing the dashboard influences students' goals. When students were presented with below- and above-average feedback on the quiz, students who saw their performance above the (artificial) class average had lower performance-avoidance achievement and performance-avoidance information-seeking orientations (Aguilar & Baek, 2019), indicating a positive influence of the above-average dashboard views.

Aghaei (2023), in a qualitative study, applied Weiner's attribution theory (Weiner, 1986) to understand the effect on students' attribution of achievement and motivation of the dashboard showing the assignment grade, time spent on an assignment, and students' ability. Consistent with social comparison research (Gerber et al., 2018), students preferred to compare themselves with students with similar or better performance. Such comparisons often led some students to negative perceptions of their abilities. However, in a selective display of lower-performing students, comparison based on attributes such as time spent and ability can lead to an attribution of low effort, resulting in a positive motivational impact.

To summarize, the existing research indicates that the impact of LADs largely depends on what students see in their view of the dashboard. As stated by Susnjak and colleagues (2022), "it is also not altogether clear what visual elements LADs should possess, that is, what type of information is effective at triggering positive behavioural adjustments in learners, or what aspects are detrimental by potentially inducing anxiety among learners" (p. 2). This study analyzes the differences in students' learning behaviours after viewing the dashboard in various states; we determine which states are positively, neutrally, or negatively associated with learners' actions.

1.3 Frame of Reference and Peer Comparison

Frames of reference are important for students to understand their data in LADs (A. F. Wise, 2014). Comparison with peers has been used the most so far (Jivet et al., 2017), as it is easy to implement and requires no additional input from the student. However, comparison with peers showed mixed preferences from students (Jivet et al., 2018), showing comparison with peers benefiting high-achieving students the most (e.g., J. P. L. Tan et al., 2016; J. Kim et al., 2016; Aguilar, 2022). However, Corrin and de Barba (2014)'s results for the class-average dashboard show that the students above the class average were demotivated by seeing their status. This result was obtained using a think-aloud protocol wherein students seeing the dashboards were asked "to articulate the actions they *would* take in response" (p. 2, emphasis ours; Corrin & de Barba, 2014), rather than observed students' behaviour after seeing the dashboard.

There is some data-based evidence that comparison with higher-achieving peers benefits lower-performing students (Davis et al., 2017) and that higher usage of peer comparison features correlates with higher activity (Brusilovsky et al., 2016; Orji & Vassileva, 2021). On the other hand, some students prefer to avoid comparing themselves with others (Tabuenca et al., 2015; A. Wise et al., 2014). Indeed, Aguilar and Baek (2019) developed a Motivated Information Seeking Questionnaire with two orientations, performance-information approach and performance-information avoidance, and showed how viewing class-average dashboards changed students' information-seeking preferences (Aguilar, 2022). Despite some negative attitudes, the question remains whether or not the comparison with peers can be desirable and beneficial and for whom.

Festinger (1954), in his *Theory of Social Comparison* (SC), states that it is human nature to seek comparison with peers and change one's behaviour following certain (empirically validated) rules. Davis and colleagues (2017), Brusilovsky and colleagues (2016), and Fleur and colleagues (2020) explicitly motivated their LAD designs by Festinger's theory. Brusilovsky and colleagues (2016)'s study tested two versions of the MasteryGrid dashboard, with and without social comparison, in the context of sizeable semester-long LAD use in a graduate class. MasteryGrid was unique in showing the *conceptual knowledge* that *individual* students mastered, displaying it in a large coloured matrix. The users in an individual peer-comparison condition attempted to solve dramatically more problems and maintained high engagement during the course; in the non-comparison LAD version, students' initial increase in activity diminished over time. A statistically significant impact of SC LAD was observed across various student learning activities. Although the learning gain was higher for the peer-comparison users, it was not statistically significant; however, weak students who used their LAD at least five times improved significantly. Orji and Vassileva (2021), in four SC conditions, observed significant increases in learning activity and performance against baseline: the highest in the "competition" (implemented as a leaderboard with accumulated performance in the course) and "upward social comparison" (showing five students with higher grades), and less in "social learning" (histogram of grades).

Gamification in education aims to increase motivation, which is associated with performance (Schneider & Preckel, 2017). Leaderboards, an often used gamification component (Dichev & Dicheva, 2017), directly implement the SC by showing a student ranked within the group of students. However, despite high attention given to gamification research over the last decade and its increase during the pandemic (Nieto-Escamez & Roldán-Tapia, 2021), only a few studies measure the direct impact of leaderboards on motivation and performance, with mixed results. To illustrate, Balci and colleagues (2022) did not find any difference in student performance on quizzes and assignments when comparing the leaderboards group with the control, although leaderboards were rated positively. While the leaderboards used by Balci and colleagues (2022) were anonymized, the ones used by Bai and colleagues (2021) showed students' names and pictures. Bai and colleagues (2021) analyzed students' responses in the top, middle, and bottom thirds of the class leaderboard (at the end of the course) in two types of leaderboards: absolute, showing all students, and relative, showing five students above and one below. The absolute students' ranking did not relate to course performance; however, top-ranked students showed more intrinsic motivation than lower-ranked. In the relative leaderboard, top students showed much higher performance than other students; however, students overall made little effort to improve their position.

In this study, two dashboards use comparison with peers: class average displays a cumulative measure of the whole class, while top contributors is a leaderboard recognizing the best students by name. The third dashboard uses an indicator not directly related to the measured reading, posting, and monitoring behaviour. Instead, it looks at the content of posted messages and how they address key discussion topics. This study contributes to our understanding of how viewing each *dashboard state*, with respect to the displayed indicators, and students' learning behaviours that are relevant to the learning activity are related.

1.4 Dashboards to Support Students in Online Discussion

As shown in Sections 1.1 and 1.2, generic measures of students' activity, such as final grades or login counts, are prevalent when assessing dashboards' impact on learning, especially on achievement (Kaliisa et al., 2024). On the other hand, LADs designed as feedback for a particular learning activity typically display measures that are activity specific and considered desirable from a pedagogical perspective (A. F. Wise, 2014).

We study LADs' impact in the context of AODs. AODs are used heavily in blended and fully online learning (Luppicini, 2007) to support critical discussions among individual learners (Loncar et al., 2014). Students' behaviours in AOD, i.e., lurking, reading, and posting, have been studied closely (e.g., Dennen, 2008; A. Wise et al., 2014). For example, 59.4% of participants in Dennen (2008)'s study stated that they lurked to find a model of participation. In small-group discussions, the problem is circular: uncovering the model depends on other students' posts, which are not forthcoming. Rovai (2007) highlighted maintaining motivation as a critical factor for sustaining students' engagement and participation. Kehrwald (2008)'s findings point to the importance of establishing, understanding, and promoting social presence in AODs. Several researchers studied how LADs can help to support students in AOD; participation levels (Bakharia et al., 2016; A. Wise et al., 2014) and interactions (J. P.-L. Tan et al., 2017; Yoo & Jin, 2020) were the most commonly displayed indicators. These LAD evaluations typically followed the summative approaches described in Section 1.1, although using measures specific to AODs, such as frequency of reading and posting, replying behaviour, or density of created social links.

A few notable studies delved deeper into understanding the impact of indicators included in the LAD on student behaviours. A. F. Wise (2014) developed nine LAD indicators of desirable AOD activity; their LAD showed the student's values and those for the class average. At the semester's end, the researchers interviewed nine students, analyzed changes in their discussion activity, and connected them to the information presented in the LAD. The study shed light on how students' viewing of particular values and states drives their behaviours. Similarly, Yoo and Jin (2020) used a comprehensive approach to design and evaluate a LAD with multiple components and used expert reviews and experience evaluation focusing on specific dashboard elements.

Findings from these studies helped us to understand how dashboard elements influenced students' behaviours in the context of a specific learning activity. However, the evaluation depended on students' accounts at the end of the course instead of traced changes in response to particular values of LAD indicators as seen in LADs. In this study, we aim to understand how seeing a dashboard with indicators above, at, or below a norm is associated with students' unfolding learning behaviours, as measured by well-established AOD metrics.

1.5 Research Questions

Prolific LAD research has unfolded in many directions, with a significant body of research focused on studying dashboards' impact on learning. The dominant approach so far has been studying students' responses to LADs as a group by comparing some measures between conditions, which has led to inconclusive results. We posit that to improve understanding of how dashboards are associated with students' learning behaviour, we need to (1) focus on individual student's learning behaviour, (2) capture and represent the content of the dashboard a student sees, and (3) observe and analyze the student's actions that follow the dashboard view in the context of well-understood learning activity. We pursue these goals by analyzing students' behaviours in response to viewing three dashboard types using different frames of reference in the context of AODs. To our knowledge, this work is the first to use this approach.

This study addresses two research questions:

RQ1: How are different frames of reference used to present comparison of dashboards for online discussion associated with students' active participation and engagement with discussion topics following the dashboard viewing?

RQ2: How is what students see on different types of dashboards regarding their performance standing associated with their following learning actions in terms of odds of posting to the discussion?

2. Methods

2.1 Context: AODs

In this study, we studied LADs' impact in the context of AODs. We designed a discussion activity by integrating several guidelines (A. F. Wise et al., 2013; A. F. Wise, 2014; Rovai, 2007; Gašević et al., 2015). Within 10 to 14 days, students in small groups of 6 to 12 were asked to formulate a shared statement to an open-ended question, such as "What are the new challenges and opportunities that the big data phenomenon brings when compared to database technology of yesterday?"[1] The participation guidelines (see Appendix A) included recommendations for the types of messages to be posted at different stages of the discussion, following the Cognitive Presence taxonomy of the Community of Inquiry framework (Garrison et al., 2001; Gašević et al., 2015). The marking scheme rewarded the quality of message content and sources used (individual mark, 40%); considering and building on ideas of others, i.e., collaboration (individual, 30%); language and tone used (individual, 10%); and quality of the final group statement (shared, 20%). These marks were scaled by the number of messages posted by students, with a minimum of four messages required to get the full mark. We worked with instructors to develop discussion activities in different courses and incorporated discussions into their respective course assessments. Each discussion was worth 5% toward the final grade.

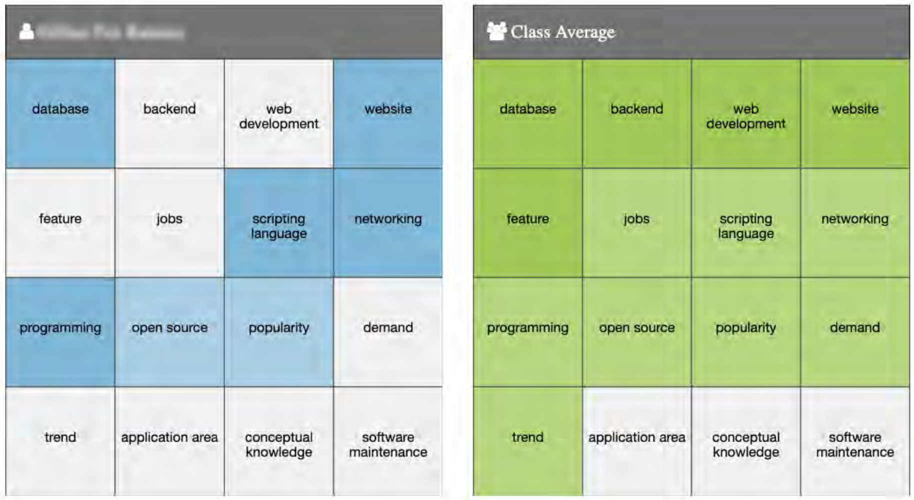
2.2 Dashboard Design

In the prior study, the source of LAD usage data for this study, we investigated if students' achievement goal orientation (AGO; Elliot et al., 2011) can be used to personalize LADs (Shirazi Beheshitha et al., 2016). We created two distinct dashboards aimed at encouraging engagement of performance-oriented students and mastery-oriented students, respectively. For the mastery-oriented students, who value the improvement of their knowledge the most, we designed the *post quality* dashboard (Figure 1a). The dashboard shows a grid of key topics for the discussion question provided by the instructor and how well the student's posts cover these topics. The colour intensity on the left indicates the cohesion of the messages covering the topic, computed using latent semantic analysis (LSA). Several examples of post quality dashboards are also shown in Figure 2. As no frame of reference for topic coverage was provided by the instructor, to give students a means to assess their progress (A. F. Wise, 2014), the right side of the dashboard shows the average topic coverage by other students' posts. Although this element introduced the comparative aspect with peers, which according to AGO theory is valued by performance-oriented students, we posit that this element in our *post quality* dashboard is content oriented, maintaining mastery orientation–guided students toward the post content, rather than quantity.

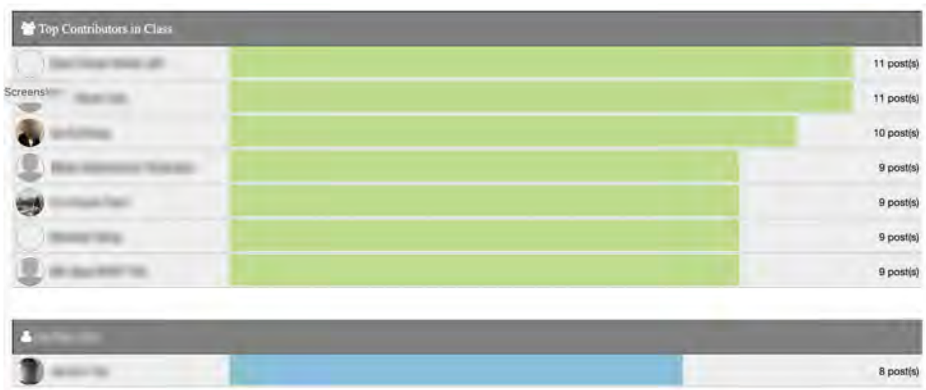
The *top contributors* dashboard (a leaderboard, Figure 1b) aligned with performance-oriented students' goals of being recognized by others (other-approach in Elliot's 3×2 AGO model). Five students with the most posts were listed by name in the dashboard (similar to "Transparent Participation Dashboard" in Jin, 2021; Bai et al., 2021). Students viewing the dashboard could see their progress below the top contributors list. Despite a minimum number of four posts specified by an instructor, several students posted more messages, up to 12. We theorized that personal recognition of top posters would resonate well with students with high performance-achievement goals.

[1] Table 11 in Appendix B lists questions in all discussions included in the study.

(a) Post quality dashboard



(b) Top contributors dashboard



(c) Class average dashboard

Figure 1. Examples of three types of dashboards.

The *class average* dashboard (Figure 1c) is widely deployed in LADs, and its impact has been studied previously (e.g., Corrin & de Barba, 2014; Aguilar, 2022). We theorized that it should appeal to performance-oriented students, with a frame of reference standard based on all peers. An expected tension existed between the minimum requirement of four messages set by the instructor and what all students believed to be an adequate level of posting to meet this requirement in the context of other course assessments and discussion mark weight overall. Given its widespread use, the class average also provided a benchmark, which is well understood in the LAD research community.

The dashboard content was generated dynamically upon each student's request, based on the discussion data retrieved at 5-minute intervals. The dashboard views were timestamped to inform students about the latest update time, and an explicit message was posted above the dashboard about the 5-minute update interval[2]. Text of the discussion messages was retrieved from the learning management system (LMS) and analyzed for keywords. The LSA algorithm computed the semantic coherence score of the messages, which was used to inform post quality dashboard visualization. Students' reading and posting activity and requests for dashboard views were logged and used for analysis in this study.

[2]Regardless of providing this information, some students complained that their post was not *immediately* reflected in the dashboard.

Table 1. Codes used for Dashboard Views based on the student's posting up to the point of viewing.

Code	Description
Class Average Dashboard	
VIEWzero	No student's posts
VIEWbelow	Student's post count bar is below the class average
VIEWat	Student's post count bar is the same as the class average
VIEWabove	Student's post count bar is above the class average
top contributors Dashboard	
VIEWzero	No student's posts
VIEW1Below	Posts count bar is one below the last person shown in the top contributors list
VIEWmBelow	Posts count bar is more than one below the last person shown in the top contributors list
VIEWinTop	Listed as one of the top contributors
Post Quality Dashboard (see Figure 2 for examples)	
VIEWzero	Student made no posts or student's post(s) did not address any key topics.
VIEW<1third	Student's posts addressed less than one third of topics addressed by classmates' posts
VIEW˜1half	Student's posts addressed about half of topics addressed by classmates' posts
VIEW>2thirds	Student's posts addressed more than two-thirds of topics addressed by classmates' posts

2.3 Participants and Source of Data

Data for this study came from small-group discussion activities embedded in second- and third-year university courses at a research-intensive, comprehensive university. Courses from information technology, human-computer interaction, media production, interactive arts, educational psychology, and media culture were included (see Table 11 in Appendix B). All courses used blended delivery, using LMSs to host course material and learning activities, including discussion forums. All course discussions used the same design, type of discussion question, requirements, guidelines, and course grade weighting (see the above section). The dashboards were accessible from the top of the discussion page via a link and a thumbnail, with text inviting students to check on their progress. Participation in discussions was mandatory; each discussion contributed 5% toward the final grade. Students were randomly assigned to one of the three dashboard conditions[3]; the dashboard assignment remained the same for the duration of the discussion activity.

All data from 21 discussion activities in 11 courses was pooled. Out of 1,119 unique discussion/student assignments, 896 students participated in the discussions, and their LMS log data was included in the analysis. A separate system for generating dashboards, linked with the LMS via the Learning Tools Interoperability (LTI) protocol, logged all students' requests to view the dashboard and the parameters used to generate the dashboard view content. Only usage data was used in this study, analyzed after obtaining secondary data ethics approval by the university research ethics board; hence, no demographic or course performance (grades) information is available for the included student sample.

2.4 Data Pre-processing and Encoding

The LMS showed all discussion posts for the group on a single page; the log record of viewing the page represents reading the discussion ("Read" action). We coded posting a top-level message and replying as a "Post" action. The request for displaying a dashboard was coded as "View Dashboard" for RQ1. For answering RQ2, we coded the "View Dashboard" more finely (see Table 1), capturing LAD's information content seen by a student and how it qualitatively communicated a *student's status* at that particular moment.

In the next step, we created and coded discussion activity sessions. We chose a 30-minute gap between two discussion actions to indicate a new session, similar to other studies (e.g., Kovanović et al., 2015; Sher et al., 2019). Figure 2 shows an example of one student's discussion activity and how it was partitioned into 15 sessions. It should be noted that we did not distinguish between gaps where a student might have been working on some other course activity (e.g., between Sessions 2 and

[3]It should be noted that in courses with two or three discussions, we have used a crossover study design. Hence, only the first-discussion dashboard assignment was randomized, and the second and third followed the crossover matrix assignment. The crossover analysis is not part of this study.

Figure 2. Example of coding a student's actions in the discussion activity for post quality dashboard. Snapshots of the dashboard show what this student saw when they viewed the dashboard.

3, separated by a day gap) or may have been doing research and composing a post for the discussion activity (e.g., between Sessions 9 and 10, with a gap slightly over 30 minutes, and Session 10 starting with a post). Next, we coded sessions using the codes in Table 1, following these rules (also see example in Figure 2):

- Sessions with only Read actions were labelled READonly.
- Sessions with Read and any number of Post actions were labelled POST.
- Sessions with View Dashboard actions, but no Post action, were labelled using code from Table 1, using the *last*[4] View Dashboard code in the session.
- Sessions containing both View Dashboard and Post actions were labelled by code where the prefix "POST+" was added to the code from Table 1, using the *last* View Dashboard code in the session. The order of Post and View Dashboard actions was ignored.

For each student, we computed counts of sessions, the number of posts made, and dashboard views. For RQ2, we used sequences of sessions as input into frequency analysis, odds of posting analysis, and odds ratio (see below).

[4]We chose the last View Dashboard code as we were interested in the student's behaviour in the session following the dashboard view.

Table 2. Model of Student Success in AOD (adapted from D. Kim et al., 2016). Proxy indicators used in this study are in bold.

Factors	Students' Behavioural & Psychological Characteristics	Proxy Indicators
Active Participation	Time investment Frequent responses Frequent visits Frequent postings	Total Time Spent on LMS LMS Visit Frequency **Discussion Board Visit Frequency** **Number of Posts**
Engagement with Discussion	Well-structured posts and replies Intensive work Interest in topics	**Posting Length** Discussion Time per Visit
Consistent Effort and Awareness	Responsibility Punctuality Time Management Intrinsic motivation	LMS Visit Interval Regularity Discussion Board Visit Interval Regularity
Interaction	Initiative Active Communication Leadership	In-Degree Centrality Out-Degree Centrality

2.5 Connecting Dashboard Views and Learning Behaviours

D. Kim and colleagues (2016), through an extensive literature review, defined four critical factors for student success in AOD: active participation, engagement with discussion topics, consistent effort and awareness, and interaction. Each factor represents a group of students' characteristics and behaviours supported by the state of the art in AOD research (Table 2; for theoretical grounding see D. Kim et al., 2016). The authors operationalized these factors through proxy indicators (Table 2, column 3). Finally, they evaluated the indicators' contribution to predicting students' low- or high-achieving status (based on the course grade) in two discussion modes: whole class and team-based discussion. In this study, we examined the two factors of "Active participation" and "Engagement with discussion" using three indicators from Table 2: Discussion board visit frequency (i.e., reading), Number of posts (i.e., posting), and Posting length.

2.6 Statistical Analyses

Students' participation in the discussion may have been influenced by the discussion topic nested within different courses, possibly affecting students' interest, the language used, the complexity of the discussion, and the suitable post length. Small discussion groups may have varied in dynamics, i.e., the timing of group members' posting affecting students' opportunity to reply to others' posts (i.e., the network effect), potentially influencing individuals' posting behaviour. Hence, to analyze the associations between the three LADs and selected variables, we used hierarchical linear mixed models (Schielzeth & Nakagawa, 2013) and the Tukey honest significant differences (Tukey HSD) test for pairwise comparisons.

First, we separated students into viewers (i.e., those who viewed a dashboard at least once) and non-viewers. We examined how the discussion behaviour of viewers differed from those of non-viewers[5]. To answer RQ1 for the three dashboard conditions, we compared proxy indicators (D. Kim et al., 2016) of "Active Participation," namely the number of sessions, number of dashboard views, and number of posts, and "Engagement with Discussion" via posting length (see Table 2). We also checked if the high-performing students did not compromise their contribution quality by posting many shorter messages.

To examine RQ2, we only considered dashboard viewers. We analyzed the sequences of the states for each student. First, we analyzed the transition matrix of sequence types for each dashboard and computed the odds of students' posting in or after the session in which they viewed the dashboard in any dashboard state. To compare how the posting behaviour after viewing the dashboard differed from when students did not see the dashboard, we computed the odds ratio as Yule's Q (Bakeman & Gottman, 1997). Yule's Q is an odds ratio ranging from -1 to 1, with 1 meaning certainty and 0 meaning a 50:50 chance. Hence, positive values of Yule's Q indicate a higher likelihood of posting after viewing a dashboard than after not viewing a dashboard.

Next, we focused on individual students and coded the dashboard views that each student saw. For each student, for each dashboard view the student saw, we computed the odds of posting after seeing this particular view and Yule's Q of posting after viewing this dashboard view as compared to not viewing it. Since not all students saw the dashboard in every state, we

[5] It should be noted that non-viewers are not a proper control group for our three dashboard conditions, as they may not have engaged with dashboards for varied reasons, including their overall lower academic interest in the course/discussion.

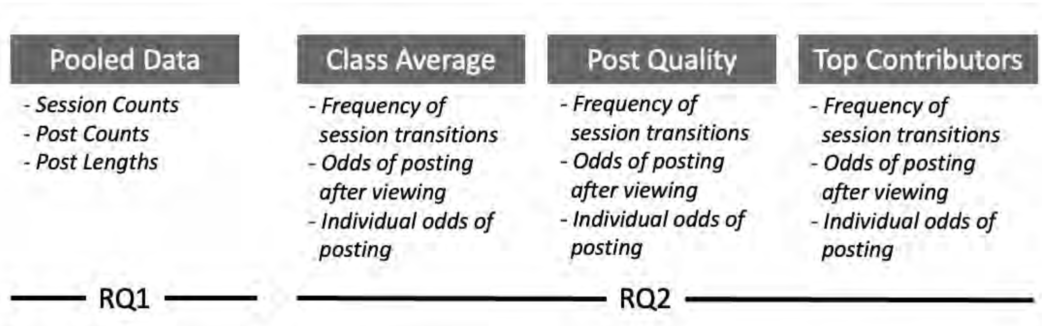


Figure 3. Method diagram for answering each RQ with indicated data analysis.

analyzed each state separately. To determine whether any particular dashboard view was more likely to be followed by students' posting than posting without a view, for each dashboard, we fitted a hierarchical linear model to compare the means of Yule's Q's for each dashboard state. For significant models, we made post hoc pairwise comparisons using Tukey HSD.

Since students were required to post a minimum of four messages to get the full mark, to account for the possibility that the student's motivation may have changed after meeting the minimum posting requirement, we also computed odds of posting and Yule's Q up to the point when students posted their fourth message. We repeated the above two analyses with these values.

3. Results

We present our results in subsections following the diagram in Figure 3. In the first subsection, we answer RQ1, followed by three subsections dedicated to answering RQ2 for each dashboard separately.

3.1 RQ1: Session, Dashboard View, and Post Counts by Dashboard Usage

Out of 1,119 dashboard/student assignments in 21 discussions, 896 students participated in the discussions, i.e., the LMS logged at least one reading or posting action in a discussion. The participants generated 28,290 log entries, of which 19,749 were reading discussions, 4,484 were posting, and 4,057 were dashboard views. 567 students viewed the dashboard at least once (so-called viewers), and 329 did not open the dashboard (non-viewers). Table 3 shows the median and first and third quartile values for the number of sessions, the number of dashboard views, and the number of posts made by non-viewers and viewers, and viewers further split for specific dashboard types. On average, viewers participated in the discussion more actively: they had more discussion sessions ($M = 34.6, SD = 23.10$) than non-viewers ($M = 18.2, SD = 15.52$); the difference was statistically significant, as confirmed by a hierarchical mixed-effect linear model with discussion topic and group membership as random effects ($F(1, 875.36) = 145.48, p < .001$). Viewers posted more messages ($M = 4.4, SD = 2.44$) than non-viewers ($M = 3.5, SD = 2.47$); this difference was statistically significant ($F(1, 875.1) = 19.08, p < .001$).

Table 3. Posting activity of dashboard viewers and non-viewers.

	N	Sessions Med (25%, 75%)	Dashboard Views Med (25%, 75%)	Posts Med (25%, 75%)
Non-viewers	329	14 (9, 22)	0 (0, 0)	4 (1, 5)
Viewers	567	30 (18.5, 46)	4 (2, 8.5)	4 (3, 6)
Class Average	112	34 (20, 49.25)	4 (2, 8)	4 (3, 6)
Post Quality	272	26 (16, 40)	3 (2, 8)	4 (3, 5)
top contributors	183	30 (20, 50)	4 (2, 8)	4 (3, 5)

Out of 567 viewers, 112 students were in the class average dashboard condition, 183 in the top contributors condition, and 272 in the post quality dashboard condition[6]. To compare discussion behaviour between conditions, i.e., the three dashboard types, we fitted hierarchical linear models with discussion topic ID and group ID as random effects. The differences in the number of sessions, number of posts, and number of visualization views were not statistically significant between the three dashboards.

[6]The lower number of participants in the class average dashboard condition stems from a glitch in the recording system for this dashboard in the first semester of experiments, forcing us to discard this portion of the data. The higher number of post quality participants results from the crossover study design with an alternative dashboard to post quality (not reported here).

Table 4. Comparison of message lengths.

Dashboard	Status	N	Med (25%, 75%)	(Mean, SD)	F-statistics
	Non-viewers	1370	121 (65, 192)	(149, 124.9)	
	Viewers	3004	131 (75, 221)	(172, 160.2)	$F(1,754.2) = 8.28, p < 0.01$
Class Average:	VIEWabove	470	132 (66, 233)	(186, 199.7)	
	not VIEWabove	255	111 (69, 185)	(144, 110.3)	$F(1,129.7) = 0.35, p = 0.56$
Post Quality:	VIEW>2thirds	176	149 (69, 266)	(195, 185.9)	
	not VIEW>2thirds	1070	126 (77, 200)	(164, 147.6)	F(1, 134.2)=3.33, p=0.07
top contributors:	VIEWinTop	138	101 (71, 242)	(168, 156.8)	
	not VIEWinTop	895	143 (83, 233)	(177, 157.1)	$F(1,113.5) = 0.80, p = 0.37$

To measure the "Engagement with Discussion," we compared the message length between conditions and for high-performing students[7]. Table 4 shows the descriptive statistics of message length for viewers and non-viewers and for students seeing themselves in the dashboard as achieving the highest status and those in other statuses. Table 12 in the supplementary tables in Appendix B shows the statistics for all states. Comparing viewers and non-viewers, the difference was statistically significant, as confirmed by a hierarchical mixed-effect linear model with discussion topic, group membership, and student[8] as random effects; none of the differences for the three dashboards were significant (see the last column of Table 4 for F statistics).

3.2 RQ2: Sequence Transitions for Class Average Dashboard

3.2.1 Class Average: Frequencies of Session Transitions and Odds of Posting

112 students used the class average dashboard and produced 1,676 session transitions. Figure 4 shows the frequencies of session transitions between session types based on the pooled data. For example, in 33 sessions, students viewed the dashboard where they saw themselves below the class average and did not post in this session (VIEWbelow, row 3). In the following session, 6.1% of students viewed the dashboard in the same state without posting (VIEWbelow column); in 48.5% of the sessions, they read the discussion without viewing the dashboard and posting (READonly); in 39.4% of the sessions, they read the discussion and posted without viewing the dashboard (POST), and in 6.1% they posted and saw themselves reaching the class average (POST+VIEWat column).

To draw more general insights about the types of actions that followed viewing the dashboard in any state, we have summarized Figure 4 in Figure 5: the "All View" column shows the frequency of transitions to sessions in which students viewed the dashboard (this includes the sessions in which they viewed and posted), and "All Post" shows the frequency of transitions to sessions in which students posted. Viewing the dashboard for students who had made zero posts or were below the class average led to the two highest percentages of transition to posting (34.8% and 43.2%). However, for these two states, the percentage of transition to viewing the dashboard is relatively low (25.8% and 15.9%), especially compared to viewing the dashboard at the class average (45.9%). A possible explanation is that after viewing the dashboard in zero and below states, students knew exactly how many messages they needed to post to reach the class average. After reaching the class average, they monitored their status and possibly aimed to improve it (25.7% transitions to posting sessions). All three posting percentages are higher than transitions to posting from ReadOnly sessions and Post sessions. Once students saw their above-average status, they seldom posted another message in the next session (15.5%) but monitored their status quite often (31.9%).

Class Average	N	VIEWabove	VIEWat	VIEWbelow	VIEWzero	ReadOnly	Post	POST+VIEWabove	POST+VIEWat	POST+VIEWbelow	POST+VIEWzero
VIEWabove	131	22.9%	0.8%	0.0%	0.0%	60.3%	7.6%	8.4%	0.0%	0.0%	0.0%
VIEWat	24	0.0%	33.3%	0.0%	0.0%	37.5%	16.7%	4.2%	4.2%	4.2%	0.0%
VIEWbelow	33	0.0%	0.0%	6.1%	0.0%	48.5%	39.4%	0.0%	6.1%	0.0%	0.0%
VIEWzero	62	0.0%	0.0%	1.6%	16.1%	46.8%	27.4%	6.5%	1.6%	0.0%	0.0%
ReadOnly	1064	4.9%	1.0%	2.1%	4.9%	66.3%	15.5%	3.6%	0.5%	0.9%	0.4%
Post	260	12.3%	0.4%	1.5%	0.0%	63.8%	16.2%	5.4%	0.4%	0.0%	0.0%
POST+VIEWabove	76	22.4%	1.3%	0.0%	0.0%	61.8%	6.6%	7.9%	0.0%	0.0%	0.0%
POST+VIEWat	11	0.0%	18.2%	18.2%	0.0%	45.5%	9.1%	9.1%	0.0%	0.0%	0.0%
POST+VIEWbelow	11	0.0%	0.0%	18.2%	0.0%	45.5%	27.3%	9.1%	0.0%	0.0%	0.0%
POST+VIEWzero	4	0.0%	0.0%	0.0%	0.0%	75.0%	0.0%	0.0%	25.0%	0.0%	0.0%

Figure 4. Frequency of session transitions for students in class average dashboard.

[7] To categorize the messages, we classified students according to their highest-seen level for each dashboard.

[8] Students are included in random effects because a student can post several messages, creating a repeated measures scenario.

Class Average	N	All View	ReadOnly	All Post
VIEWabove	207	31.9%	60.9%	15.5%
VIEWat	35	45.7%	40.0%	25.7%
VIEWbelow	44	15.9%	47.7%	43.2%
VIEWzero	66	25.8%	48.5%	34.8%
ReadOnly	1064	18.2%	66.3%	20.9%
Post	260	20.0%	63.8%	21.9%

Figure 5. Summarized frequency of session transitions for students in class average dashboard.

Table 5. Counts of session posting and not posting after viewing and not viewing class average dashboard.

	Posting in Next Session	Not Posting	Odds of Posting
Viewing	83	269	0.31
Not Viewing	279	1,045	0.27

Table 5 shows counts of transitions for all viewers of the class average dashboard, where viewing of the dashboard in one session was followed by a session in which they posted. The odds of posting were higher after viewing the dashboard (0.31 vs. 0.27); the odds ratio was 1.156, and Yule's Q was 0.072, indicating that students were more likely to post after viewing the dashboard.

3.2.2 Class Average: Individual Odds of Posting

The previous analyses considered data pooled from all students. We also computed the odds of posting and Yule's Q for each student and each dashboard view state separately. Table 6 shows summative values for each dashboard state viewed. The values were computed (1) for all student sessions and (2) for the number of sessions until the student reached the four posts set as a minimum by the instructor. Compared to the overall odds of posting after viewing the class average dashboard (i.e., 0.31), when analyzing students individually, viewing the dashboard in states VIEWzero, VIEWbelow, and VIEWat had higher odds of posting, both before the student posted the four required messages and overall (mean values of odds are in Table 6). However, before reaching four posts, only views with no posts and below average had a positive Yule's Q ($YQ4 = 0.25$ and $YQ4 = 0.62$, respectively), indicating that the odds of posting after seeing these views were higher than the odds of posting without seeing the dashboard in the previous session. It is worth noting that the only dashboard view after which the students were less likely to post was VIEWabove, with $YQ = -0.45$.

Table 6. Class average dashboard: Summative statistics of odds of posting and Yule's Q computed for each individual student.

Dashboard View	All Sessions: Odds of Posting Mean, SD, *n*	All Sessions: Yule's Q (YQ) Mean, SD, *n*	Session up to 4 Posts: Odds of Posting Mean, SD, *n*	Session up to 4 Posts: Yule's Q (YQ4) Mean, SD, *n*
VIEWabove	0.24, 0.30, 56	−0.45, 0.72, 36	0.22, 0.34, 37	−0.57, 0.62, 23
VIEWat	**0.47**[a], 0.43, 19	**0.05**, 0.66, 13	0.45, 0.47, 16	−0.26, 0.70, 12
VIEWbelow	**0.65**, 0.45, 39	**0.65**, 0.37, 15	**0.64**, 0.46, 38	**0.62**, 0.45, 12
VIEWzero	**0.47**, 0.48, 56	**0.13**, 0.77, 30	**0.47**, 0.48, 56	**0.25**, 0.70, 23

[a] The bolded values indicate states with higher odds of posting and higher likelihood than the generic dashboard view without distinguishing states.

To compare if any dashboard view is more likely to be followed by posting than other views, we fitted a hierarchical linear model with discussion ID as a random effect to compare the means of Yule's Q for each dashboard state. The students' likelihood of posting after seeing the dashboard in different states was significantly different for the whole discussion duration, $F(3,94) = 10.49, p < .001$, as well as until students posted their fourth message, $F(3,70) = 11.45, p < .001$. A post hoc test revealed that for the whole duration, seeing the dashboard in the state where students were above average (VIEWabove) was significantly less likely to be followed by posting than the same state where students were below average and with the class average at zero (VIEWbelow, $p < .001$, VIEWzero, $p = .002$). When considering only sessions before students posted their fourth message, similar pairwise comparisons were observed; i.e., seeing the dashboard in the state where students were above average (VIEWabove) was significantly less likely to be followed by posting compared with the same state where students were below average and with the class average at zero (VIEWbelow and VIEWzero, both $p = .031$). The likelihood of posting after viewing the dashboard at the class average (VIEWat) was significantly lower than below average (VIEWbelow), $p = 0.004$.

Post Quality	N	VIEW>2thirds	VIEW~half	VIEW<1third	VIEWZero	VIEWnoViz	ReadOnly	Post	POST+VIEW>2thirds	POST+VIEW~half	POST+VIEW<1third	POST+VIEWZero	POST+VIEWnoViz
VIEW>2thirds	43	34.9%	4.7%	0.0%	0.0%	0.0%	44.2%	9.3%	7.0%	0.0%	0.0%	0.0%	0.0%
VIEW~half	148	0.0%	20.9%	1.4%	0.0%	0.0%	56.8%	8.8%	2.0%	9.5%	0.7%	0.0%	0.0%
VIEW<1third	147	0.0%	0.7%	16.3%	0.0%	0.0%	59.9%	9.5%	0.7%	7.5%	5.4%	0.0%	0.0%
VIEWZero	233	0.0%	0.0%	0.0%	22.7%	0.0%	45.5%	15.5%	1.7%	5.6%	6.0%	3.0%	0.0%
VIEWnoViz	44	0.0%	0.0%	0.0%	18.2%	6.8%	63.6%	6.8%	0.0%	2.3%	2.3%	0.0%	0.0%
ReadOnly	2500	0.5%	2.4%	3.2%	6.6%	1.6%	66.8%	13.4%	0.5%	1.6%	2.2%	1.2%	0.0%
Post	521	0.4%	4.4%	4.0%	1.2%	0.0%	69.9%	16.7%	1.0%	1.0%	1.0%	0.6%	0.0%
POST+VIEW>2thirds	36	36.1%	5.6%	0.0%	0.0%	0.0%	44.4%	8.3%	5.6%	0.0%	0.0%	0.0%	0.0%
POST+VIEW~half	96	1.0%	27.1%	0.0%	0.0%	0.0%	49.0%	9.4%	4.2%	9.4%	0.0%	0.0%	0.0%
POST+VIEW<1third	96	0.0%	1.0%	19.8%	0.0%	0.0%	59.4%	8.3%	1.0%	2.1%	8.3%	0.0%	0.0%
POST+VIEWZero	43	0.0%	2.3%	2.3%	4.7%	0.0%	53.5%	20.9%	0.0%	2.3%	9.3%	4.7%	0.0%
POST+VIEWnoViz	1	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 6. Frequency of session transitions for students in post quality dashboard.

Post Quality	N	All View	ReadOnly	All Post
VIEW>2thirds	79	46.8%	44.3%	15.2%
VIEW~half	244	37.3%	53.7%	21.7%
VIEW<1third	243	31.3%	59.7%	21.8%
VIEWZero	276	37.0%	46.7%	32.6%
VIEWnoViz	45	31.1%	62.2%	11.1%
ReadOnly	2500	19.8%	66.8%	19.0%
Post	521	13.4%	69.9%	20.2%

Figure 7. Summarized frequency of session transitions for students in post quality dashboard.

3.3 RQ2: Sequence Transitions for Post Quality Dashboard

3.3.1 Post Quality: Frequencies of Session Transitions and Odds of Posting

272 students used the post quality dashboard and produced 3,908 session transitions; Figure 6 shows the frequencies of transitions between the sessions. Figure 7 summarizes the transitions for the dashboard states, as was done for the class average dashboard. It should be reiterated that students viewing the post quality dashboard were unaware of the number of posts their classmates made on average. With that in mind, the posting behaviour that followed viewing the dashboard was informed by reporting the content of students' posts. Viewing the dashboard where the student had not posted yet (VIEWzero) was followed in 32.6% of cases by sessions in which the student posted. Seeing the dashboard where students' highlighted keywords were less than a third or about half of those highlighted for the class was followed by posting in over 21% of cases, comparable with posting activity after not seeing the dashboard (ReadOnly and Post states). Seeing a well-populated dashboard indicating the high quality of students' posts (>2thirds) was followed by posting in only 15.2% of cases. On the other hand, the post quality dashboard is highly engaging; after viewing it, students viewed it again in the following session in more than 30% of cases and as high as 46.8% for the >2thirds status.

Table 7. Counts of session posting and not posting after viewing and not viewing post quality dashboard.

	Posting in Next Session	Not Posting	Odds of Posting
Viewing	213	674	0.32
Not Viewing	579	2,442	0.24

Table 7 shows counts of transitions for all viewers of the post quality dashboard, where viewing the dashboard in one session was followed by posting in the next session. The odds of posting were higher after viewing the dashboard (0.32 vs. 0.24); the odds ratio was 1.333, and Yule's Q was 0.143, indicating that students were more likely to post after viewing the dashboard.

3.3.2 Post Quality: Individual Odds of Posting

Table 8 shows individual odds of posting computed similarly to the class average dashboard (Section 3.2.2). Analyzing students individually showed that viewing the dashboard in states where a student had not posted yet or did not mention any keywords in their posts (VIEWzero), or their view showed that their messages had more than two-thirds of keywords identified for class (VIEW>2thirds), had higher odds of posting after seeing such views ($M = 0.48$ and $M = 0.42$, respectively). However, the positive Yule's Q ($YQ = 0.33$) was seen only in the VIEWzero state, indicating a higher likelihood of posting after seeing the dashboard in this state than not seeing the dashboard before posting. We observed the same outcome for sessions of up to four messages posted.

Table 8. Post quality dashboard: Summative statistics of odds of posting and Yule's Q computed for each individual student.

Dashboard View	All Sessions: Odds of Posting Mean, SD, n	All Sessions: Yule's Q (YQ) Mean, SD, n	Session up to 4 Posts: Odds of Posting Mean, SD, n	Session up to 4 Posts: Yule's Q (YQ4) Mean, SD, n
VIEW>2thirds	0.42, 0.44, 25	−0.29, 0.62, 18	0.34, 0.44, 12	−0.47, 0.60, 8
VIEW˜half	0.31, 0.37, 93	−0.21, 0.68, 66	0.34, 0.39, 70	−0.20, 0.73, 53
VIEW<1third	0.20, 0.34, 93	−0.43, 0.65, 46	0.25, 0.37, 76	−0.29, 0.70, 36
VIEWzero	**0.48**, 0.45, 191	**0.33**, 0.70, 85	**0.48**, 0.45, 190	**0.28**, 0.70, 69

The bolded values indicate states with higher odds of posting and higher likelihood as compared to the generic dashboard view without distinguishing states.

The students' likelihood of posting after seeing the dashboard in different states was significantly different for whole discussion sessions, $F(3,215) = 16.11, p < .001$, as well as until students posted their fourth message, $F(3,166) = 8.21, p < .001$. The post hocs revealed that viewing the dashboard before posting their first message (VIEWzero) was significantly more likely followed by posting than after viewing in dashboards with less than one-third and about half (both $p < .001$), and above two-thirds ($p = 0.002$) of keywords in their messages highlighted compared with keywords in the class messages. The post hoc test p values for the same pairwise comparisons in the model up to posting the fourth message were $p < .001$, $p = .001$, and $p = 0.018$, respectively.

3.4 RQ2: Sequence Transitions for Top Contributors Dashboard

3.4.1 Top Contributors: Frequencies of Session Transitions and Odds of Posting

183 students used the top contributors dashboard and produced 3,062 session transitions. Figure 8 shows the frequencies of session transitions for the top contributors dashboard.

Figure 9 summarizes transitions for view states, as done for the two dashboards above. Students who saw themselves in the top contributors' group viewed the dashboard in the next session in a staggering 69.2% of cases. Similarly high was monitoring behaviour for students who were just one post behind the top group. Surprisingly, after viewing their status, students in this group rarely posted in the next session (only 10.7%) to reach the top contributors' group and become listed and recognized by all in the class. It should be noted that the top contributors were a highly select and small group of students, five or a few more when there was a tie of posts for the fifth position, in the class of 40 to 120 students. On the other hand, seeing the dashboard where students were two or more posts behind the top group was followed by posting in 23.9% of cases, which is higher than after the ReadOnly session and comparable to the "Post" session.

Top Contributors	N	VIEWinTop	VIEW1Below	VIEWmBelow	VIEWnoViz	ReadOnly	Post	POST+VIEWinTop	POST+VIEW1Below	POST+VIEWmBelow	POST+VIEWnoViz
VIEWinTop	32	46.9%	9.4%	0.0%	0.0%	25.0%	3.1%	9.4%	6.3%	0.0%	0.0%
VIEW1Below	47	0.0%	31.9%	12.8%	0.0%	44.7%	2.1%	4.3%	0.0%	4.3%	0.0%
VIEWmBelow	362	0.0%	0.0%	14.4%	0.0%	59.1%	12.7%	1.1%	4.1%	8.6%	0.0%
VIEWnoViz	74	0.0%	0.0%	12.2%	10.8%	67.6%	6.8%	0.0%	0.0%	1.4%	1.4%
ReadOnly	1961	0.3%	0.6%	11.2%	3.3%	67.0%	12.4%	0.2%	0.8%	4.1%	0.2%
Post	384	0.3%	0.8%	8.6%	0.0%	65.6%	19.3%	1.0%	0.8%	3.6%	0.0%
POST+VIEWinTop	20	55.0%	5.0%	0.0%	0.0%	30.0%	5.0%	5.0%	0.0%	0.0%	0.0%
POST+VIEW1Below	37	0.0%	29.7%	8.1%	0.0%	51.4%	5.4%	5.4%	0.0%	0.0%	0.0%
POST+VIEWmBelow	141	0.0%	1.4%	28.4%	0.0%	53.2%	7.1%	0.0%	1.4%	8.5%	0.0%
POST+VIEWnoViz	4	0.0%	0.0%	0.0%	25.0%	50.0%	25.0%	0.0%	0.0%	0.0%	0.0%

Figure 8. Frequency of session transitions for students in top contributors dashboard.

Top Contributors	N	All View	ReadOnly	All Post
VIEWinTop	52	69.2%	26.9%	15.4%
VIEW1Below	84	48.8%	47.6%	10.7%
VIEWmBelow	503	31.4%	57.5%	23.9%
VIEWnoViz	78	25.6%	66.7%	10.3%
ReadOnly	1961	20.7%	67.0%	17.6%
Post	384	15.1%	65.6%	24.7%

Figure 9. Summarized frequency of session transitions for students in top contributors dashboard.

Table 9. Counts of session posting and not posting after viewing and not viewing top contributors dashboard.

	Posting in Next Session	Not Posting	Odds of Posting
Viewing Dashboard	145	572	0.25
Not Viewing Dashboard	441	1,904	0.23

Table 9 shows counts of transitions for all viewers of the top contributors dashboard, where viewing the dashboard in one session was followed by posting in the next session. The odds of posting were higher after viewing the dashboard; the odds ratio was 1.094, and Yule's Q was 0.0451, indicating that students were more likely to post after viewing the dashboard.

Table 10 shows individual odds of posting computed similarly to the class average dashboard (Section 3.2.2). Compared to overall odds of posting after viewing the top contributors dashboard (0.25), when analyzing students individually, only viewing the dashboard where a student was more than one post below showed the higher odds ratio $M = 0.31$ and positive Yule's Q $YQ = 0.66$. The same observation applies to the situation until students post their fourth message ($M = 0.36, YQ4 = 0.73$).

Table 10. Summative statistics of odds of posting and Yule's Q computed for each individual student in the top contributors dashboard.

Dashboard View	All Sessions: Odds of Posting Mean, SD, n	All Sessions: Yule's Q Mean, SD, n	Session up to 4 Posts: Odds of Posting Mean, SD, n	Session up to 4 Posts: Yule's Q Mean, SD, n
VIEWinTop	0.23, 0.31, 12	−0.60, 0.62, 10	0.00, 0.00, 5	−1.00, 0.00, 4
VIEW1Below	0.18, 0.36, 35	−0.77, 0.51, 29	0.11, 0.30, 23	−0.81, 0.51, 19
VIEWmBelow	**0.31**, 0.37, 149	**0.66**, 0.61, 50	**0.36**, 0.40, 139	**0.73**, 0.56, 36
VIEWnoViz	0.13, 0.32, 66	−0.73, 0.60, 32	0.13, 0.32, 66	−0.78, 0.52, 29

The bolded values indicate states with higher odds of posting and higher likelihood as compared to the generic dashboard view without distinguishing states.

Students' likelihood of posting after seeing the dashboard in different states was significantly different for whole discussion sessions ($F(3,121) = 56.92, p < .001$), and also for until the four-message limit was reached ($F(3,88) = 63.99, p < .001$). A post hoc test revealed that students who saw themselves lagging more than one post behind the top contributors' group (VIEWmBelow) were significantly more likely to post than when they saw themselves just one post behind the top group (VIEW1Below) or in the top group (VIEWinTOP), or if they viewed visualization before the top group had been established (VIEWnoViz), all $p < .001$. No other significant pairwise differences were found for the three remaining states. The same pairwise comparison results were observed for the model before students posted their fourth message.

4. Discussion and Future Directions

The main overarching insight from this research is that dashboard viewers, as opposed to non-viewers, are significantly more engaged in discussion activity regarding the number of sessions and are more likely to post after viewing the dashboard. This observation is consistent across dashboards with different frames of reference. Other dashboards have been found supportive of engagement and participation (e.g., Brusilovsky et al., 2016; Aljohani et al., 2019; Han et al., 2021). This study's novel contribution is discovering unique activity patterns that follow dashboard viewing, using three kinds of dashboards and two frames of reference. The observed patterns differ if a student sees themself at the lower, middle, or high end of the frame of reference used for presenting the student's status in the dashboard.

Given that all students were assigned to one of the three dashboards, this usage study had no control group. Nevertheless, some students never opened the link to the dashboard (non-viewers), which allows for some comparison, with a caution that this may indicate an overall lower level of academic engagement. Comparison between dashboard users and non-users is commonly done in dashboard research, albeit critiqued for its inherent deficiencies (Kaliisa et al., 2024). Notably, given that the marking criteria required a minimum of four messages for full marks, both dashboard viewers and non-viewers posted a median of four messages. However, the bottom quarter of the non-viewers posted only one message compared with viewers, who posted three messages. Similarly, the top quarter of viewers posted more messages than non-viewers, i.e., six messages vs. five.

However, given this similarity in the number of messages posted, we observed that viewers participated much more actively in the discussion. This is indicated by more than doubling the number of sessions during the 2-week discussion period (30 vs. 14). Viewing the discussion without posting allows students to obtain the model for participation, check for replies, and reflect (Dennen, 2008). The act of "listening," i.e., attending to others' messages without posting, is critical for knowledge construction and is a part of active participation (A. F. Wise et al., 2013). Other research has found the number of visits to indicate active discussion participation (Hung, 2008; Webb et al., 2004) and to be a strong predictor of midterm and final exam scores (Cheng et al., 2011). In D. Kim and colleagues (2016)'s prediction models for a team-based discussion course, a similar context to ours, the frequency of the discussion board visits had the highest predictive power for student success in the first part of the course, and it was the second most important variable in the second part of the course. Interestingly, we saw a doubling of the number of sessions when compared with non-viewers (median 14 sessions), even as none of our dashboards showed this metric, i.e., two of our dashboards focused on the number of posts (34 sessions for class average and 30 for top contributors), and one dashboard focused on the level of keywords covered in the students' posts (26 sessions for post quality).

Although attending to other posts and visiting the discussion often is vital for students' learning, there would be nothing to attend to without posting. The posting behaviour creates the material based on which the students' learning unfolds. Before we address our findings about the posting behaviours, we discuss the message length, a proxy indicator for "Engagement with Topics" (Table 2). Xie (2013) showed how message length strongly correlated with other measures of engagement. For a student to write a sufficiently long message requires carrying out necessary research and considering others' ideas; simultaneously, a longer message creates sufficient space for students to be cognitively engaged through argumentation and justification (Shukor et al., 2014). On the other hand, with the stated requirement of the number of posts (four in our discussions) and with two dashboards prioritizing the number of posts, students may tend to compromise the length of their messages to meet the quantitative requirement or advance their status shown in the dashboard (in class average and top contributors). However, we have not observed statistically significant differences in posting length between dashboard conditions, nor the highest status seen by the student in the dashboard (Tables 4 and 12). In class average and post quality, the messages posted by the two highest statuses had higher means than the lower statuses, although this difference was not statistically significant. In the top contributors dashboard, the messages were slightly shorter for students in the top status ($M = 168$) than for students who did not reach the top status ($M = 177$). We can conclude that in the dashboards providing feedback regarding the number of posts we did not observe significantly shorter messages. For completeness, we found that viewers posted longer messages than non-viewers; the difference was statistically significant, with viewers posting on average 15% longer messages (149 vs. 172).

The class average dashboards are ubiquitous in the gradebooks of LMSs such as Canvas and Moodle and have been studied the most. However, none of the studies so far have examined how *the views of the dashboard* are related to students' behaviour in the context of actual courses. Hence, our findings are novel in this regard and further expand on those of Corrin and de Barba (2014), who found that students, hypothetically, would be demotivated by seeing themselves as above average. Although this is true for the posting behaviour, we observed high continuing engagement and activity monitoring after the above-average dashboard views. Our observation also aligns with Aguilar (2022)'s finding that above-average views decrease students' hesitation to seek comparative information.

We have also observed how the top contributors dashboard—a leaderboard—had the highest positive association with following posting for students not shown in the leaderboard and high monitoring activity for the "leading" students. In general, our findings corroborate the findings of several studies (e.g., Orji & Vassileva, 2021; Bai et al., 2021) about the positive impact of the leaderboard-type dashboard. In particular, while Bai and colleagues (2021) in their relative leaderboards found students not interested in improving their position, we have seen the students who viewed their status as below the top group in the leaderboard as most associated with posting, with Yule's Q of 0.66. In contrast to Philpott and Son (2022), who observed a ceiling effect of students disengaging when the maximum number of points was reached for their leaderboard, we saw only a small drop in Yule's Q after students reached a minimum of four posts (from 0.73 to 0.66). Additionally, the top students in the top contributors remain highly active in the discussion, with 69% continuing to monitor their state in the dashboard. It should be noted that our research method differs from other studies that considered the impact of the leaderboard on overall class performance. Instead, we provide insights about the behaviours immediately following students' viewing the leaderboard.

The discovered patterns for our post quality dashboard are not easily compared to other research due to their specificity for the discussion activity. We can conclude that the post quality dashboard has high captivating power. Students are very likely to continue viewing it, possibly to see their posts' concepts coverage compared with the class. This behaviour can be explained by students monitoring to see that they keep their good standing. However, we have not observed higher likelihood of posting after seeing the populated dashboard; only when students see their dashboard without keywords were they more likely to post than without seeing it. Although the dashboard points students toward important keywords, it is not motivating enough to post more when compared with sessions without viewing the dashboard.

One of the contributions of this study is understanding how viewing a dashboard in a particular state is associated with the likelihood of students' posting. Indeed, we found that some dashboard views increase the odds of students' posting while others decrease it. However, overall, we saw students' "Active Participation" increase in the discussion activity. To what extent are our results transferable to support other learning activities? First, our dashboards present one of several types of possible measurements related to the activity, i.e., the number of posts or the number of covered keywords. More importantly, the information in the dashboard represents feedback directly actionable by a student (Hattie & Timperley, 2007). The change in student status is shown in absolute numbers rather than as a percentage, making it easy for students to connect the presented information with possible action. From this perspective, our dashboard is similar to those used in Kia and colleagues (2020), or the Private Participation Dashboard in Jin (2021). As for the students' response to seeing themselves performing at a particular level concerning the frame of reference, we expect our findings to be replicable in other learning activities.

Our findings point to several possible future research directions. First, they provide further support for pursuing research in personalizing the dashboard presentations to individual students (see, e.g., Teasley, 2017). However, as we have shown, each type of dashboard has its own "motivation" profile, and our research only looked at three different LAD types in the context of AOD and was correlational in nature. More detailed research is needed to understand how presenting comparative information through varied frames of reference impacts students' motivation. Each dashboard in our study included only a single indicator of the learning activity. As many dashboards are complex and present varied indicators, unpacking the impact of viewing their combinations becomes increasingly complex. Should the practice pursue the development of a collection of well-understood simple dashboards and personalize their selection for students? Or, should we strive to better understand the impact of the complex dashboards with many, possibly conflicting, indicators? The research so far has predominantly pursued the second direction mainly through summative descriptive evaluations. We suggest that researchers should strive to capture the actual LAD views by students and analyze those views to better understand the LAD's impact on learners' behaviours. Another direction is to look at individual students' characteristics. As learners' goals very much drive motivation (Hidi & Renninger, 2019), another potential research direction toward personalization is to study how students with different goals respond to the dashboards in different states (e.g., Shirazi Beheshitha et al., 2016).

4.1 Limitations

Our study pooled data from several courses. Even as discussion activity in these courses followed the same format, provided the same guidelines, and contributed to the final grade with the same weight, we have not considered different contexts that could have influenced students' behaviour. Our designed dashboards were specific for the discussion activity. For clarity of this research, they included only one measure of participation in the learning activity: either a count of student's posts (class average and top contributors dashboards) or a quality measure of students' posts (post quality dashboard). This choice can make our results relevant for other types of dashboards showing a single measure, possibly in a different learning activity. However, the effects of more complex dashboards showing different student standings with various measures need to be carefully studied and better understood.

Additionally, our findings are general to the extent of how actionable the information presented in the dashboards is. All our dashboards pointed students directly at how to improve their standing in the learning activity: the class average and top contributors dashboards showed the number of student posts, which could be changed by posting another message; the post quality dashboard showed keywords that were not covered well in the student's posts and could be corrected directly by focusing their next posts on these keywords. A similar situation is often presented through counts (e.g., exercises attempted and solved) or lists of items to be addressed (e.g., topic mastery). However, we believe the direct connection between the metric and the student's action must be present for our results to apply. Indeed, these suppositions need to be experimentally confirmed in other settings.

5. Conclusions

We studied students' behaviour after viewing dashboards integrated into graded online small-group discussions. We reconstructed the exact content of each dashboard for each student's view and classified the result as performing below, at, or above the norm used by the dashboard. Three different dashboards with three norms, i.e., class average, the top discussion contributors, and quality of message content, constituted the three conditions. The frequency of transitions between sessions revealed to what extent each dashboard state was followed by the desired action in the discussion, i.e., posting, and how often students viewed the dashboard in the subsequent session.

There are three main contributions of this study that add to the state of the art in LAD research. First, the methodology used in this study is unique in reconstructing the exact view the students saw in the dashboard and analyzing students' following behaviour based on their status as seen in the dashboard. This approach led to two critical findings that expand our understanding of how dashboard views precede students' participation in the discussion activity. Different information presented in the dashboard, as determined by the selected frame of reference, and the student's own position within that frame are associated with what students will do next. Second, our findings provide the most detailed understanding of how two commonly used frames of reference function: the class average and most active learners types of dashboards. Third, we have shown how our findings can point to further study of personalized dashboard selection mechanisms to maintain high engagement and active participation in online discussions.

Declaration of Conflicting Interest

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1. Appendix A: Discussion Participation Guidance

Discussion Participation Guidance

You are expected to engage in the discussion that will explore different aspects of the question itself, propose different ideas to address these aspects, select some ideas and justify why these were included and other rejected, and finally decide on the answer with a clear rationale.

Everyone is expected to participate meaningfully in the discussion. You are asked to post **at least** 4 times. Your contributions have to be at the appropriate level and depth. The following contributions are expected at each level:

- **Identify** aspects to explore (1-3 messages from each participant) – engage in an analysis of the question being asked, as a group come with set of aspects that should be explored to address the question.
- **Explore** ideas to address the aspects (2-4 messages each) – do individual research to explore the aspects, integrate material from the readings for the class, and post your finding to share with others. Read others' posts, build on their ideas or argue the points they brought up by bringing new evidence or interpreting existing evidence and points in the discussion so far.
- **Integrate** ideas (1-3 posts each) – participate in constructing a meaningful response from ideas raised in the previous posts. Select well-supported ideas to use in shaping group's position on the question, decide on the way to structure the response.
- **Final statement** – 1 message for the group posted by ***wrapper*** role. Each group selects a wrapper.

Expectations and Marking

You are expected to post a minimum of 4 posts as follows. To get the discussion going, we recommend that you post **minimum 1 post within first 2 days, minimum 2 posts on days 3-5.** For expected quality of messages see the marking rubric below. This discussion activity is worth 5% of the course mark. The 5% comprises of the following components:

Quantity – Reading and posting as specified for each message category. The rest of the marks will be scaled based on number of posts: 4+ posts (100%), 3 posts (75%), 2 posts (50%), etc.

If majority of your messages is posted close to the deadline, these will be discounted.

Quality

- 40% **Content** – based on posts within each category (Identify, Explore, Integrate)
  - ***Below average:*** Message tends to address peripheral issues and/or ramble. Tendency to recite facts and provide opinions. Relevant concepts not discussed *.
  - ***Average***: Messages tend to provide good general contributions, but may not always directly address discussion topics. Assertions are not always supported by evidence. Relevant concepts included into the discussion but not strongly connected to other logically related ideas*.
  - ***Above average***: Messages are characterized by conciseness, clarity of argument, depth of insight into theoretical issues, originality of treatment, relevancy, and sometimes include unusual insights. Relevant concepts included into the discussion and connected well to other logically related ideas.
- 30% **Collaboration** – Engaging in the dialogue with others' ideas presented in the posts.
- 10% **Tone & Mechanics** – Conducting yourself appropriately in a professional relationship. The messages are carefully formulated with minimum of spelling and grammatical errors.

Summary

- 20% **Quality of arguments** in the final response– shared by all group members.
- The **wrapper** will receive up to 1% extra mark for their work.

2. Appendix B: Supplementary tables

Table 11. Examples of small-group discussion questions included in the study.

Course topic (year)	Discussion question(s)
Internet Technologies (3rd)	• In a course like <code>, is it or is it not important that students learn how to program web applications in the programming/scripting language X? • What are the new challenges and opportunities that the big data phenomenon brings when compared to database technology of yesterday? • Cloud computing is one of the new buzzwords in the internet computing community. Is it just a new name for the old set of technologies, or does it represent a significant breakthrough that takes computing to the new level?
New Media (2nd)	• Analyze each of three short films according to key elements discussed by Bordwell and Thompson in Chapter 3 Narrative Form. Argue for and against different possible interpretations and as a group arrive at a conclusion. Summarize your reasoning in the one team post at the end.
Media across Cultures (2nd)	• How does othering (the act of deciding that someone is “Other”) manifest itself in Vancouver today? • Explore the two dominant models for North American multiculturalism: the “melting pot” and the “cultural mosaic.” Which of these two models is the most accurate social model to reflect contemporary Canadian society? Which of these models is the most desirable? Is there another model that might better represent your ideals? As a group develop your position with arguments based on references, concrete examples, and your own personal experiences. Look at articles, videos, and online sources.
Interactive Arts (2nd)	• In “Strategies of Interactivity” Daniels outlines seven models of interaction used in artworks from the 1980s onwards. In this assignment you will explore several contemporary examples of interactive artworks and discuss with your peers what models of interaction they employ based on Daniels’ models.
Communications (2nd)	• Identify traditional and new creative firms in Vancouver to glean how they use new and social media differently. For example, does a movie theatre use social media differently to promote its product than a games manufacturer? What is important to do here is to look at the types of messages these organizations use. For example: Do they run contests? Does their messaging read like advertising or does it read like community-building? What sort of voice does the organization have?
Educational Psychology (2nd)	• Thinking about the ideas put forth in the Chapter 8 Point/Counterpoint, take a stand on whether memorizing information exactly is an effective learning strategy. Justify your choice with evidence from the textbook. Try to specify a particular context to think about and make sure to make a choice for one option or the other in your initial posting. • Thinking about the ideas in the Chapter 10 Point/Counterpoint, take a stand on whether inquiry learning methods such as problem-based learning should be used instead of more traditional methods of teaching and learning. In your argument try to identify situations or conditions in which inquiry learning methods would be more effective or less effective. As always, provide evidence and reasons to support your position.
HCI & Cognition (2nd)	• There are many different design options for navigation in complex web pages. Currently, scrolling web pages are “in vogue,” but tab-based designs, menu/navigation bars, “hamburger” navigation menus, or other options exist, and some pages even mix multiple options. Your objective is to explore the appropriateness of the various options (scrolling pages, tab-based, menu-based, hamburger, etc.). Which option is better suited for which user population? Which of these options is more appropriate for which context? Which of these options is better for different device sizes (ranging from smart watches to wall-sized displays)? Which of these options is better for different input modalities? • Moving all information and computing into digital systems seems attractive. Yet, we all use external means, such as writing things down, sketching and doodling on paper, sticky notes, and asking other people about their knowledge and/or for help with problem solving, to augment our interaction with computer-based systems. Your objective is to explore the continuum between digital systems and the real world. Which options are more appropriate for which context? Which option is better suited for which user population? Do the trade-offs change with different device size (ranging from smart watches to tabletop-sized displays and even wall-sized displays) or with different input modalities?

Table 12. Comparison of length of posts by students according to their highest viewed status viewed in the dashboard.

Dashboard	Status	N	Med (25%, 75%)	(Mean, SD)	F-statistics
Class Average:	VIEWabove	470	132 (66, 233)	(186, 199.7)	
	VIEWat	32	150 (117, 244)	(183, 115.7)	
	VIEWbelow	101	106 (77, 185)	(146, 113.0)	
	VIEWZero	122	95 (64, 168)	(133, 104.9)	$F(3, 154.5) = 1.23, p = 0.30$
Post Quality:	VIEW>2thirds	176	149 (69, 266)	(195, 185.9)	
	VIEW˜1half	393	134 (79, 227)	(185, 181.4)	
	VIEW<1third	349	129 (81, 158)	(158, 126.4)	
	VIEWzero	290	122 (73, 196)	(153, 122.9)	$F(3, 147.8) = 2.00, p = 0.12$
Top Contributors:	VIEWinTop	138	101 (71, 242)	(168, 156.8)	
	VIEW1Below	183	134 (74, 204)	(170, 171.9)	
	VIEWmBelow	580	149 (87, 240)	(184, 159.7)	
	VIEWnoViz	57	127 (76, 174)	(148, 118.7)	$F(3, 135.5) = 1.22, p = 0.31$