# How Patterns of Students Dashboard Use Are Related to Their Achievement and Self-Regulatory Engagement

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## ABSTRACT

The aim of student-facing dashboards is to support learning by providing students with actionable information and promoting self-regulated learning. We created a new dashboard design aligned with SRL theory, called MyLA, to better understand how students use a learning analytics tool. We conducted sequence analysis on students' interactions with three different visualizations in the dashboard, implemented in a LMS, for a large number of students (860) in ten courses representing different disciplines. To evaluate different students' experiences with the dashboard, we computed chi-squared tests of independence on dashboard users (52%) to find frequent patterns that discriminate students by their differences in academic achievement and self-regulated learning behaviors. The results revealed discriminating patterns in dashboard use among different levels of academic achievement and self-regulated learning, particularly for low achieving students and high self-regulated learners. Our findings highlight the importance of differences in students' experience with a student-facing dashboard, and emphasize that one size does not fit all in the design of learning analytics tools.

## CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **Information visualization**; • **Applied computing →** *Interactive learning environments*;

## KEYWORDS

Student-facing dashboard, sequential pattern mining, self-regulated learning, academic achievement

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## 1 INTRODUCTION

Increasing use of technology in education and the resulting ability to keep track of learning activities offer the opportunity to understand students' behaviors at an unprecedented level of analysis and scale. Learning analytics dashboards (LADs) have emerged from a growing interest in presenting and visualizing students' learning activities in digital learning environments [42]. They emerged as one of the first direct applications of learning analytics, designed to inform educators and administrators about students' performance [10] and to support decision-making related to increasing student retention [42].

Based on research showing that students experiencing a higher level of control in the learning process are more likely to be intrinsically motivated and improve their performance [38], student-facing dashboards are growing in popularity, for both residential and online courses, to promote student agency and support learning [21, 51]. Although student-facing dashboards are rapidly entering the higher education marketplace, research on their effectiveness is at an early stage. Recent meta-reviews of student-facing dashboard research have revealed that there are few empirical studies on the impact of dashboards on student motivation, behavior, and skills [5, 10, 42, 47]. Furthermore, the research has been concentrated more on dashboard usability and usefulness rather than understanding how they can support educational practices [16]. Only a few recent studies have investigated the impact of learners' differences in using dashboard information [3, 20], such as learning tactics and strategies [18], and most dashboards have a "one size fits all" design [45].

Given the problems identified in extant reviews, the present study contributes to the growing research on student-facing dashboards in several ways. First, we focused on **theory** [43], asking how a dashboard could be designed to provide actionable information that supports self-regulated learning (SRL) [23, 28], which has been shown to be critically related to academic performance [40]. Second, for a dashboard we called "My Learning Analytics" (MyLA), we designed the visualizations following the principles of good **information visualization design** [27, 29, 30], using perceptually effective visual encodings and consistent graphical schemas to reduce cognitive load [31, 32]. Third, based on both log and survey data, our research design allowed us to **evaluate students' differences** that would have impacted on their experience with information in the dashboard. Our study highlights the importance of students' differences in dashboard use behavior for a large number of students in courses representing different disciplines. Students' academic achievement and self-regulatory behavior were associated with students' differences in experience using the dashboard. Particularly, low achieving students used the visualization that supported metacognitive monitoring more than did their peers, and high self-regulated learners used more frequently a number of different visualizations.

## 2 BACKGROUND

An analytics dashboard provides a visual display of the important information needed to achieve one or more goals, consolidated and arranged on a single screen so the information can be monitored at a glance [12]. In educational contexts, these displays are seen as powerful metacognitive tools, and delivering them to learners is intended to support awareness and decision-making, and trigger self-reflection by making information actionable [9, 46]. Student-facing dashboards typically provide visualizations of the students' own activity with online tools (e.g., overall LMS activity or use of specific tools) and performance (e.g., grades). In most systems, this data is shown as a comparison to classmates, thereby emphasizing competition with peers, although little is known about the effects of providing comparative feedback information to students via dashboards [45]. The designs of these visualizations are quite variable, including line graphs, bar charts, gauges, dials, heat maps, and more. What they have in common is the underlying goal for the dashboard to support student learning.

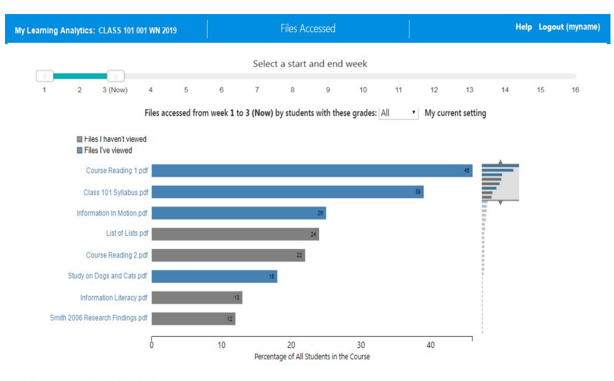


Figure 1: Files Accessed View

A study by [35] showed that while students would like more information about course deadlines and other organization supports, there was no consensus about whether notification about learning activities would be motivating, and many students specified that they did not want to have comparative performance feedback. [26] found that students' exposure to comparative information viewed on an academic advisor's dashboard may have contributed to decreasing mastery orientation. [2] provided performance dashboards to students considered to be "at risk" by their university program and found that these students were sensitive to comparative information, although they said that they would it seek it out if offered in a LMS. [22] examined how students' prior academic performance affected their opinions about dashboard views that showed comparative information. While most students found the dashboard visualizations informative, there were differences between students reported potential use of the dashboard and how they interpreted the impact of the information provided, particularly when the visualization presented performance information that was inconsistent with their prior course grades.

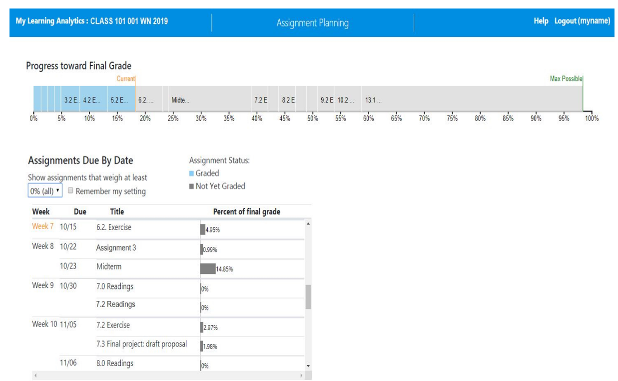


Figure 2: Assignment Planning View

Despite the growing popularity of incorporating student-facing dashboards into Learning Management Systems, several meta-reviews have indicated a number of critical issues with respect to their design and impact. [41] reviewed 55 dashboard studies of which 28 focused on student use. Across all dashboards, they found that over half of the studies failed to include a specific reference to a pedagogical approach or describe an evaluation of their use. [6] conducted a review of 93 student-facing dashboards that looked specifically at learning analytics systems that collect click-level student data and report this data directly to students. They also concluded that there were omissions in these reports: only 6% described a needs analysis, 11% reported outcomes of usability testing, and 16% examined the effects of system use on student behavior. Further, reviews provided by [5] and [24, 28] took specific issue with the lack of underlying learning theory as lens for designing student-facing dashboards and understanding the outcomes of dashboard use [48].

## 3 DASHBOARD DESIGN

Using design principles derived from Self-Regulated Learning (SRL) theory combined with a focus on accessible and actionable information, we created three dashboard views intended to support specific self-regulated learning constructs, namely motivation, planning, and metacognitive monitoring. The first view is called "*Files Accessed*" (Figure 1), displaying students' progress with respect to keeping up on assigned course materials. This view was especially designed to support students in their metacognitive monitoring of their progress. The second view, called "*Assignment Planning*" (Figure 2), was designed as a tool for students to keep track of their upcoming assignments and to monitor their progress with respect to their performance on graded items. The aim is to help students’ with their planning skills by providing information about their upcoming assignments and their performance on their prior assignments. We also included a "*Grade Distribution*" view (Figure 3) because this is the most typical performance information provided in student dashboards, and one that prior research has shown that students access frequently [13, 51]. In this view, we intended to encourage students to be motivated to succeed in their courses. Each view could be accessed from the course home page in the campus LMS, Canvas, or from the relevant page view in Canvas (Resources, Assignments, Grades).

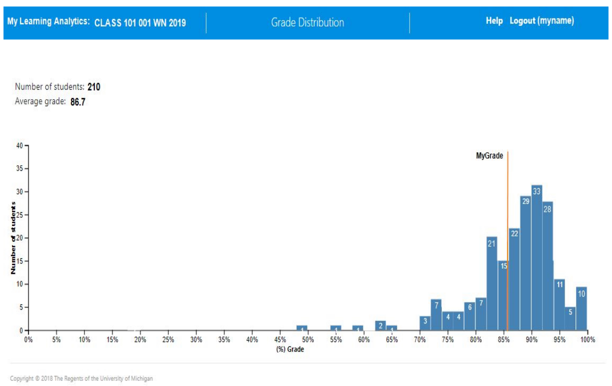


**Figure 3: Grade Distribution View**

Because our design was intended to support mastery goals over performance goals [11], all three visualizations displayed the percentage of points earned instead of letter grades. In addition, we offered students a degree of control over the information presented by allowing them to choose various aspects of what they could see, such as specifying which students’ files use is displayed (the whole class or only those students with 70-80%, 80-90%, or 90-100% of possible points), and determining the date range and weight of the upcoming graded events, including assignments, tests, quizzes, and reports.

We made consistent use of visual encodings across designs, so that students could learn how to interpret a particular visualization type and use this knowledge across all of the visualizations [31, 32]. We adopted bar charts for most subcharts, as people are very accurate at reading position along a common baseline [8, 27]. Within each dashboard we used consistent colors to encode information across subcharts; for example, in the *Files Accessed* View (Figure 2), light blue refers to *graded assignments*, gray to *ungraded assignments*, and yellow to the *current week* in both sub charts (Progress toward Final Grade and Assignments by Due Date). This way, students can learn this color mapping once and apply it to both charts, reducing the cognitive load of using the dashboard [31].

We iterated on the design of the visualizations with team members who varied in academic role (faculty, students, and IT staff) and expertise (regarding motivation and self-regulated learning theory, data visualization, and system development) making sure with every version that each view was generated with accurate data available from the LMS. Prototypes of the dashboard were designed in Tableau, and the final version was implemented in JavaScript and D3. We piloted the dashboard in three courses in the Fall 2018 term, and used the resulting data to make minor modifications and refine our research protocol. This paper describes the outcome of our full implementation of MyLA in ten courses in the Winter 2019 term.

# 4 RESEARCH QUESTIONS

This study examined the effect of students’ differences on dashboard use behavior guided by the following research questions:

***RQ1.*** *Are there discriminating patterns in dashboard use for students with differences in academic achievement?*
***RQ2.*** *Are there discriminating patterns in dashboard use for students with differences in self-regulated learning (SRL)?*
***RQ3.*** *Are students’ differences in achievement and SRL associated with specific patterns of dashboard use?*

# 5 METHODS

## 5.1 Participants

We recruited 860 students from ten courses offered in the Winter 2019 term, at a large residential research university in the United States. The dashboard was available to these students between the $6^{th}$ to $11^{th}$ week of a 16 week term, where the start date was determined by the instructors. The two courses with the shortest availability were half term courses (8 weeks). Eight courses were at the undergraduate level and two were graduate-level courses, and represented a diversity of disciplines, including architecture, engineering, science, kinesiology, and information. Courses varied in size from 19 to 265 students. Just over half of the students (52%) used the dashboard at least once (n= 449) and 19% of those students had only single interaction with the dashboard. 63% of users are male and 37% are female students.

## 5.2 Procedure

A researcher from our team presented a demo of the dashboard to each course, showing the students MyLA’s three views (shown above) and highlighting the specific features of each. Students were informed that their dashboard use would not be visible or reported to their course instructor. The dashboard was turned on at the first course meeting after the demo and was turned off at the end of the semester. Students’ interactions with MyLA were logged. At the end of the semester, the students were asked to fill out a survey.

## 5.3 Measures

*Performance Data.* At the end of the semester, we collected the cumulative Grade Point Average (GPA) as an overall measure of academic achievement for all students who used MyLA at least once. The students were categorized into high, mid-high, mid-low, and low performance groups based on their cumulative GPAs using quartiles, which divided the data into successive fourths: .25, .50, .75, and 1.00 [19]. The median was used since it is more resilient to outliers. The minimum cumulative GPA is 1.738 and maximum is 4.182. Table 1 shows the distribution of the students’ achievement levels.

**Table 1: Students' achievement levels by quartiles based on cumulative GPAs, Mdn (25%, 75%) = 3.486 (3.146, 3.727)**

| Achievement Level | Quartile Range | N (Students) |
|---|---|---|
| High | 3.727- 4.182 | 111 |
| Mid-high | 3.486- 3.727 | 113 |
| Mid-low | 3.146- 3.486 | 112 |
| Low | 1.738- 3.146 | 113 |

*Survey Data.* A survey administered at the end of the semester in *Qualtrics* was delivered via email invitation to all students enrolled in the ten classes. Participation in the survey was voluntary: 215 out of 449 students who used the dashboard (48%) completed the survey. The participants were asked about their self-regulated learning behaviors using 4 survey items measuring SRL constructs (i.e., motivation, planning, monitoring, and regulating) based on well-established scales [33]. For this study, we were concerned with not overburdening students with a long survey and accordingly selected single items to represent each of the specific SRL constructs that our dashboard design targeted. There is evidence that single items can be just as reliable and valid as multi-item scales [15]. The responses were recorded on a 5 point frequency scale, from 0 (never) to 4 (very frequently). One item assessed motivation ("I tried to motivate myself when necessary to learn the material"), and three items assessed metacognition: planning ("I planned how to study new topics before learning the material in the class"), monitoring ("I checked how well I had learned what I needed to know"), regulation ("I slowed down and took my time when something was difficult"). The four scores for each sub-scale were used to create a measure of students' self-regulatory behaviors. Then, agglomerative hierarchical clustering was applied with four SRL features, i.e., the score for motivation, planning, monitoring, and regulation. We identified three groups of students in terms of their self-regulatory behavior, i.e. high, moderate, and low self-regulated learners.

Figure 4 demonstrates three clusters of self-regulated learning behavior generated from the responses to the survey. High self-regulating students reported that they more frequently regulated their motivation, as well as planning, monitoring and adapting behaviors (cluster 3). The moderate (cluster 2) and low (cluster 1) of self-regulating students are those who reported lower levels of self-regulatory behaviors respectively. The size of clusters was not even. Most of the students (150 out of 215) were moderate self-regulated learners. There were 41 students in the low self-regulating cluster and 24 students were in the highly self-regulating cluster.

*Usage Data.* To understand the students' interactions with the dashboard, we collected log data of every learning event in MyLA, including students' interactions with the three views (i.e. *Files Accessed* (F), *Assignment Planning* (A), and *Grade Distribution* (G)). These data allowed us to look both at the frequency of use for each view, as well as examining the sequences of students interactions with the views. The order of students' choices of actions through time can be more meaningful than frequency of a certain action to understand students' learning behavior [36]. [1] introduced the concept of event sequence to find frequent customers' purchase sequences. An event sequence is considered to be an ordered list

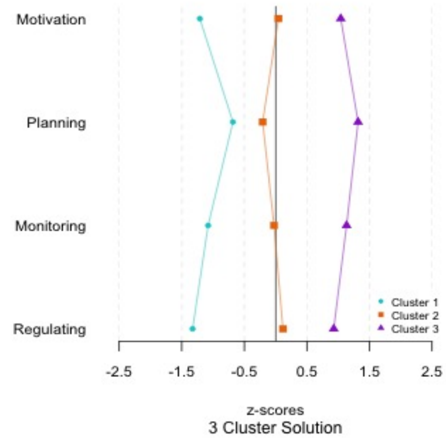


**Figure 4: Three-cluster solution based on students' self-reported SRL measure**

of time stamped events that occurs throughout a period of time. In learning analytics, a similar approach can be applied to explore students' event sequences in order to better understand their learning behaviors in online learning environments. Recent studies have adopted a sequence analysis method to examine students' online learning behaviors [17, 25, 44]. In the present study, we performed sequence analyses to provide a deeper insight into students' experience with the different kinds of information presented in the dashboard.

## 5.4 Data Analysis

The event sequences of students' interactions with MyLA were computed by performing sequence analysis [14]. Every student has one event sequence. The length of event sequences is different ranging from a single event to 135 events depending on students' frequency of dashboard use. These streams of click events were divided into sessions. We defined the students' interactions with the dashboard by session to consider the differences of the same sequences of events that occurred in a different time frame representing two different learning behaviors. The cutoff for a dashboard session was defined as ten minutes, determined by data of the students' dashboard use, which was clustered in this time frame with a typical length of ~5 minutes. If there was an elapsed time of more than ten minutes, subsequent events were considered to be within the next session of dashboard use. This cutoff determined within session versus subsequent session data in the event logs. Closely consecutive learning events within one session are shown as $(e_1, e_2)$, and two subsequent sessions with elapsed time greater than ten minutes are represented as $(e_1, e_2) - (e_3)$.

We were interested in finding frequent sub-sequences or patterns (we use both terms interchangeably) in our event sequence dataset. A sub-sequence of sequence x is an event sequence that is formed by a subset of the events of x, which respects the order of the events in x. For example, if a student clicks on (Files Accessed,

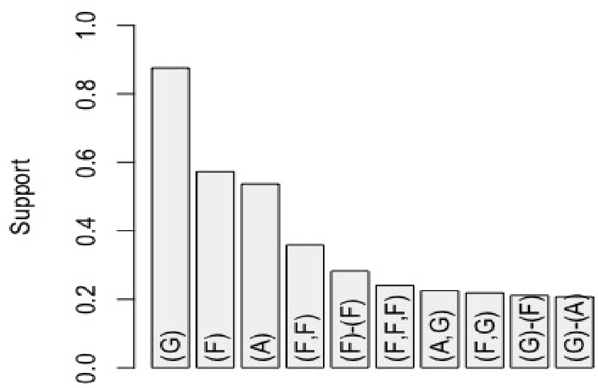


**Figure 5: Top 10 most frequent patterns in dashboard use**

Grade Distribution), it is a sub-sequence of (Files Accessed, Grade Distribution)-(Files Accessed), where the second Files Accessed is in a following subsequent session. The *support* number of a sub-sequence is defined by the number of sequences to which a sub-sequence belongs, divided by the total number of the sequences. In this study, the minimum support was set to .05 (a pattern must belong to at least 5% of the event sequences).

To address *RQ1*, we examined whether there is an association between the students' performance achievement, represented by their cumulative GPA, and their dashboard use. The analysis was carried out on the event sequences for total number of students dashboard users (n = 449). Next we carried out chi-square tests of independence to identify any frequent sub-sequences or patterns that discriminate students by their performance achievement (high, mid-high, mid-low, and low performance as explained above in Subsection 5.3). A Bonferroni correction was applied to post-hoc tests used in the analyses.

For *RQ2*, we investigated the event sequence dataset to identify sub-sequences that most significantly discriminate between groups of students with differences in their SRL. Because SRL was calculated using students' (voluntary) survey responses, here we analyzed only the event sequences of those who participated in the survey (n= 215). These students were categorized into three groups of high, moderate, and low self-regulating learners as described in Subsection 5.3. We then conducted chi-square tests of independence, and applied Bonferroni corrections, to identify patterns that discriminate SRL cohorts.

Concerning *RQ3*, we examined whether students' differences in academic achievement and SRL resulted in specific patterns of dashboard use, as prior SRL research has found that self-regulated learning is positively related to academic achievement [34]. To achieve this goal, we computed chi-squared tests of independence on frequent sub-sequences of the students, who participated in the survey study, to find if there are specific patterns for different performance and SRL cohorts. We discuss the results in the following Section.

**Table 2: Patterns discriminating dashboard use by academic achievement, $^{***}$ $p < .001$, $^{**}$ $p < .01$, $^{*}$ $p < .05$**

| Pattern | $\chi^2$ | Support under Independence |
|---|---|---|
| (F,F)-(G)*** | 43.58 | .07 |
| (F,F)*** | 42.47 | .36 |
| (A,F,F)*** | 34.07 | .08 |
| (F,F,F)*** | 34.22 | .24 |
| (F)*** | 29.96 | .57 |
| (F)-(G)*** | 29.49 | .15 |
| (F,G)*** | 28.07 | .21 |
| (A)*** | 27.01 | .54 |
| (A,F)*** | 26.52 | .20 |
| (F,F)-(F)** | 21.77 | .16 |
| (G)-(A)** | 20.03 | .21 |
| (F,F,F,F)** | 19.60 | .14 |
| (A,G)** | 19.56 | .22 |
| (A,F,G)* | 19.20 | .09 |
| (G)-(F,F)* | 19.15 | .11 |
| (A,A)* | 19.03 | .13 |
| (F,F)-(A)* | 18.69 | .07 |
| (F)-(A)* | 18.08 | .14 |
| (F,F)-(F,F)* | 17.57 | .09 |
| (F)-(F,F,F)* | 17.39 | .12 |
| (F,F,G)* | 17.28 | .10 |
| (F)-(F)* | 16.56 | .28 |

## 6 RESULTS

The exploratory sequential analysis was conducted on 449 students' event sequences to identify frequent sub-sequences of interacting with the three views: *Files Accessed* (F), *Assignment Planning* (A), and *Grade Distribution* (G). Figure 5 shows the top ten most frequent sub-sequences found. As shown in Figure 5, *Grade Distribution* was the most frequent sub-sequence (*support = .87*). The second and third places are *Files Accessed* (*support =.57*) and *Assignment Planning* (*support=.54*) views respectively. These three single event sub-sequences are the only patterns that occurred in more than 50% of event sequences. Although the next three patterns each have less than 40% support of the sequences, they belong to sequences of viewing *Files Accessed*. The rest of patterns belong to viewing *Grade Distribution* combined with either viewing *Files Accessed* or *Assignment Planning* views interchangeably.

### 6.1 RQ1. Are there discriminating patterns in dashboard use for students with differences in academic achievement?

The chi-square tests of independence were calculated on frequent sub-sequences (*minimum support = .05*) to examine whether there is any association between students' patterns and their academic achievement. The results showed that there are significant associations between students' academic achievement and multiple patterns of dashboard use. The list of discriminating patterns is shown in Table 2 (horizontal lines represent p-value cutoffs). The (Files Accessed, Files Accessed)-(Grade Distribution) pattern most significantly discriminated the students' use with differences in academic achievement ($\chi^2$ *= 43.58, p < .001*). The remaining discriminating patterns also include *Files Accessed* more than two other views occur in one session. Moreover, most of these discriminating patterns show successive views of *Files Accessed* in a single session. The *Files Accessed* view provided students with a list of learning resources accessed by them and/or their peers. These successive views of *Files Accessed* when students opened a link to a files and then returned to the *Files Accessed* view to look at more files. This sequence of actions may represent an intentional use of *Files Accessed* view more so than a single view of this view. The event log generated by our student-facing dashboard does not yet capture links to the specific files the students clicked. This data will be captured in a future version of MyLA that can help us to examine further the successive views of *Files Accessed*.

Figure 6 demonstrates the patterns that are significantly more frequent in low achieving students than expected under independence of students' difference in academic achievement. The associated colors in the bar chart define sign and significance of Pearson's residuals. Blue demonstrates that the pattern is significantly more frequent than expected under independence, and any pattern that is significantly less frequent than expected under independence appears in red. There is no pattern in other levels of students' achievement that is either significantly more or less frequent than expected under independence except this pattern: (Assignment Planning, Assignment Planning), which is significantly less frequent in high achieving students (*r = -3.22*). The results indicate that the lowest achieving students used the dashboard more actively than any other groups of students. Moreover, the frequency of patterns is negatively associated with the students' achievement levels.

Furthermore, the results indicated that low achieving students had a higher frequency of the patterns that including viewing the *Files Accessed* visualization more than once within a session. *Grade Distribution* was also viewed more than *Assignment Planning* visualization among the significantly more frequent patterns in the low achieving group. Moreover, the patterns, such as (Files Accessed, Files Accessed)-(Grade Distribution); (Assignment Planning, Files Accessed, Files Accessed); (Assignment Planning, Files Accessed, Grade Distribution), were not very frequent patterns among the students under independence (*support = .07, .08, .09*). They were significantly more frequent among the low achieving students (*r = 5.45, 4.81, 3.45*) but not among the higher-achieving students. On the contrary, (Grade Distribution)—the most frequent pattern—is not among the discriminating patterns since it occurred among almost all of the sequences (*support = .87*). Therefore, its frequency does not discriminate students by their academic achievement ($\chi^2$ *= 1.61, p = 1*) as its support among the high, mid-high, mid-low, and low achieving groups was similar (*supports = .86, .85, .90, .88* respectively).

## 6.2 RQ2. Are there discriminating patterns in dashboard use for students with differences in self-regulated learning behavior?

The chi-square tests of independence were computed on frequent sub-sequences (*minimum support = .05*) to determine whether there

**Table 3: Patterns discriminating dashboard use by SRL measure, $^{***}$ *p < .001*, $^{**}$ *p < .01*, $^{*}$ *p < .05***

| Pattern | $\chi^2$ | Support under Independence |
|---|---|---|
| (F)-(F,G)*** | 24.47 | .08 |
| (F)-(A)** | 21.33 | .19 |
| (F)-(G)** | 20.01 | .16 |
| (A,F)** | 18.55 | .24 |
| (G)-(A)* | 15.77 | .25 |
| (F,G)* | 15.20 | .22 |
| (F)-(A,F)* | 14.48 | .08 |

**Table 4: Contingency table of achievement and SRL levels in the survey study**

| SRL/ Performance | High | Mid-high | Mid-low | Low |
|---|---|---|---|---|
| High | 9 | 6 | 6 | 3 |
| Moderate | 48 | 37 | 36 | 29 |
| Low | 12 | 12 | 7 | 10 |
| Total | 69 | 55 | 49 | 42 |

are patterns that discriminate the students' dashboard use by their self-regulated learning behavior. The results revealed seven patterns that differentiate dashboard use by self-regulatory behaviors (shown in Table 3). The (Files Accessed)-(Files Accessed, Grade Distribution) pattern is the most significantly discriminating pattern ($\chi^2$ *= 24.47, p < .001*).

Figure 7 demonstrates the discriminating patterns among different self-regulating learners. There are multiple use patterns that are significantly more frequent in high self-regulating learners than expected under independence of differences in self-regulated learning behaviors. However, there are no patterns in the moderate and low self-regulating learners that are either significantly more or less frequent than expected under independence.

Furthermore, the frequency of patterns is positively associated with high and low self-regulating learners, with the exception of the moderate self-regulating group (see Figure 7). The discriminatory patterns are less frequent among moderate self-regulating learners than low self-regulating learners. Moreover, viewing *Files Accessed* belongs to 6 out of 7 discriminating patterns, mostly followed by either the *Grade Distribution* or *Assignment Planning* view. High self-regulated learners are those who are effective in metacognitive monitoring processes as the most important component of SRL. The results supported SRL research [50] since the high self-regulated group viewed more frequently *Files Accessed* view, which was designed to support students in their monitoring processes. Moreover, the high self-regulated group has a significantly higher frequency of (Assignment Planning, Files Accessed) than their peers.

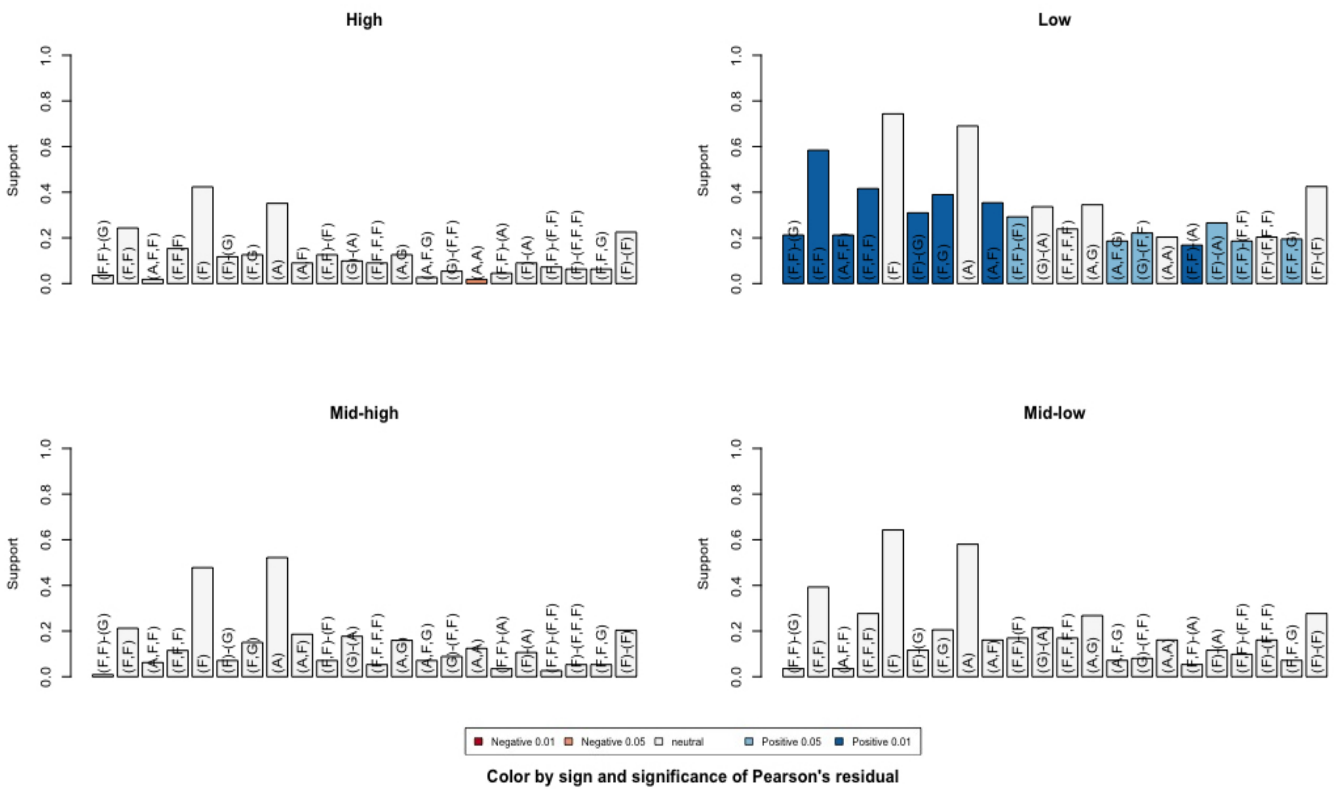


**Figure 6: The Pearson's residual of discriminating patterns among four levels of performance achievement**

## 6.3 RQ3. Are students' differences in achievement and SRL associated with specific patterns of dashboard use?

Since survey data does not include all students who used MyLA, we computed chi-squared tests (n = 215) to determine common discriminating patterns among achievement and SRL levels. The results do not show any discriminating patterns among achievement and SRL groups either collectively or separately. The chi-squared tests computed on only students' achievement levels did not reveal any similar discriminating patterns found in *RQ1.* To investigate further, we calculated chi-squared test on students' achievement and SRL levels to determine the association between these two factors. We did not also find an association between academic achievement and self-reported SRL levels ($\chi^2$ *= 2.43, p = .88*) among the students participating in the survey study. The contingency table is shown in Table 4.

# 7 DISCUSSION

The present study contributes to the research on student-facing dashboards, specifically by evaluating students' experience with a new dashboard, called MyLA, and analyzing their interactions with the three different visualizations designed to support self-regulated learning. Using both log and survey data from student users in ten different university courses, we framed our study around three research questions to capture students' learning experience.

Before addressing the research questions, we conducted an exploratory analysis to determine if students did indeed use MyLA. The log data showed that just over half of the students offered access to the dashboard used it at least once. Among the MyLA users, 87% of students viewed *Grade Distribution* visualization at least once within a session. Prior research has also shown that students access grade distributions frequently [13, 52]. In fact, students' grade distribution is the most typical (and sometimes only) performance information provided in student-facing dashboards. However, the students also looked at the two visualizations designed specifically to support SRL behaviors. The *Files Accessed* view was the second most frequent view among the students, which was designed to support metacognitive monitoring processes. The third most frequent view, *Assignment Planning*, was designed to scaffold students' SRL planning skills.

Regarding the first research question, we examined the association between students' academic achievement and dashboard use behaviors. The results indicated that low achieving students had significantly higher use of certain patterns than would be expected under independence, particularly the use of *Files Accessed* and *Grade Distribution* over the *Assignment Planning* view. This suggests that low achieving students may have been more interested in monitoring the highly accessed learning resources and their own standing in the class, rather than in planning for their assignments. Moreover, the discriminating patterns of MyLA use

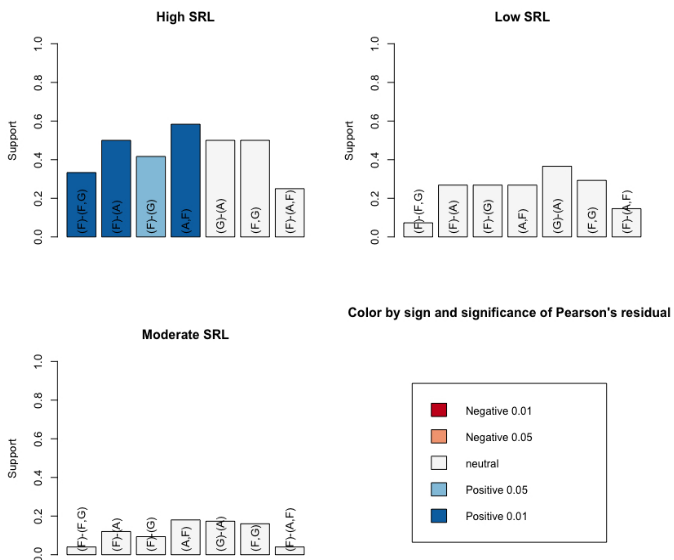


**Figure 7: The Pearson's residual of discriminating patterns among three levels of SRL measure**

suggested that successive use of the *Files Accessed* view can be used to discriminate students by their academic achievement.

Concerning the second research question, we investigated the association between students' SRL behaviors and dashboard use. The discriminating patterns that emerged from the sequential analysis showed that high self-regulating learners had significantly higher use of the *Files Accessed* and *Assignment Planning* views over the *Grade Distribution* view. This supports prior research that has shown that high self-regulated learners are more effective learners in their metacognitive monitoring processes as the most important component of self-regulated learning [50]. Another interesting finding from the discriminating patterns that emerged for different SRL cohorts is that there are seven discriminating patterns and, among those, four of them have a significantly higher frequency of use for the high self-regulating group. We also found that there were more discriminating patterns for students' academic achievement. Specifically, there were 22 discriminating patterns and, among those, 14 patterns have a significantly higher frequency of use by low achieving students. This suggests that students' self-regulated learning behaviors have more discriminatory power than their academic achievement, particularly for the high self-regulated group that can be discriminated by only 4 patterns of dashboard use.

Finally, to address to third research question about the differences in use with respect to both SRL and achievement, we conducted our analysis on the 215 students who both participated in the survey and used the dashboard. The results did not support prior SRL research that has shown that self-regulated learning is critically related to academic achievement [40]. As shown in Table 4, 71% of low and mid-low achieving students collectively reported a moderate level of SRL and almost 10% of those reported a high level of SRL. On the contrary, only 12% of high and mid-high achieving students reported a high level of SRL and 19% reported low level of SRL. However, research on SRL measures has shown that learners can be inaccurate in calibrating their self-reported SRL behaviors [37, 49, 53]. In addition, [4] reported findings consistent with ours that higher performers tend to underestimate their learning process, whereas students with lower performance tend to overestimate it.

Overall, our study has demonstrated not only how one can design a dashboard that supports self-regulation behaviors but also shown the importance of differences in students' experience with this tool. In particular, it is important to consider students' current SRL behaviors and academic achievement to understand how the dashboard might be used by different students, reflecting their different needs. These findings emphasize that one size does not fit all in design of learning analytics tools.

## 7.1 Study Limitations

The present work is the first study of our new dashboard, MyLA. One limitation of this study is that we were unable to integrate the MyLA event log with the LMS event log, which prevented us from investigating the relationships between students' use of MyLA and their other activities occurring in the LMS. Following the recent work by [7], adding LMS data to MyLA log data will allow us to use additional behavioral indicators to represent SRL behaviors. Since disagreements exist regarding SRL measurement, particularly whether self-reports represent a valid and reliable approach to measure this process, several researchers have advocated the use of behavioral indicators of SRL [53]. The review by [37] found that granularity is an important concept in the comparison of SRL measurements, influencing the degree to which students can accurately report their use of SRL strategies. Self-reported SRL measures may give a relatively accurate insight into students' global level of self-regulation. By contrast, when students are asked to report on specific SRL strategies, behavioral measures may give a more accurate account. Since we used a global measure of SRL in this study, our students' self-reported SRL was still informative. However, our future studies of MyLA can expand the research on behavioral SRL measurement by focusing on students' behavior with the three different views of MyLA along with their LMS data.

Another limitation was that the dashboard was available for students' use on a course-by-course basis, preventing them from developing practices of use across all of their enrolled courses. In fact, the single most frequent reason given for not using MyLA was that students simply forgot about it. As we scale up the dashboard implementation we will be able to provide information to students across all enrolled courses, making it more likely that students will expect to find and therefore look for the tool in the LMS.

Although our ten courses ranged across different disciplines, the study is also limited by being conducted at a single university. As a large, research-intensive university with very competitive admissions, these students represent learners who have already developed a high level of academic skill. In fact, the first quartile of our students' cumulative GPAs (the lowest performance group) is just above 3.0 on a 4-point grade scale. However, our survey data shows that these same students do not necessarily report frequent use of self-regulatory behaviors, and we did find that the low achieving students used the dashboard in a specific way more frequently (using the *Files Accessed* view) and more frequently than their higher achieving peers. This suggests that students who are under-performing relative to their peers in this competitive environment do seek additional support that dashboards can provide. Finally, as with all studies where participation is voluntary, the results may be influenced by the self-selection of MyLA users and survey responders.

## 7.2 Future Directions

Our immediate next steps are already in progress. In the current semester, we have ten courses that will be using MyLA and we will follow the research protocol described here. We did find discrete clusters of students based on four SRL scores and discriminating patterns of behavior related to these clusters. More items may have made these patterns and relationships stronger, but these four did point to findings that we believe deserve further study. We have made one design change: on the *Grade Distribution* view we have used a k-anonymity binning strategy [39] for the representation of the lowest performing students to decrease the likelihood that they could be identified by their peers, a concern particularly in small classes. Rather than setting an arbitrary minimum course size to protect students anonymity, we will be evaluating this method for displaying the lowest performers' (aggregated) data.

From the outset, MyLA has been deliberately designed to be able to expand on our campus and to other UNIZIN schools (see https://unizin.org/about/), and eventually to any Canvas-using institution. At this point in time, seven UNIZIN schools are already testing MyLA or planning to do so within the next year. As MyLA is an open source project, we have already begun to receive code contributions from other institutions interested in extending the MyLA visualizations to support their needs. Based on this level of interest, UNIZIN is considering becoming the hosting organization for MyLA implementations and is supporting our efforts to coordinate research across institutions. Three additional non-UNIZIN schools have also contacted us.

Given the extensive penetration of Canvas in the LMS marketplace in the US and worldwide, such adoptions could have a major impact. Expanding our dataset as the MyLA implementation grows will allow us to better understand the relationship between dashboard use and student achievement with a much larger and more diverse set of students. The resultant feedback from use tracking and survey information would be significant for its potential to improve dashboard functionality, including improving student agency by extending the options for customization. In addition, the design principles themselves could undergo further examination and provide further data relevant to the fields of motivation and SRL.

## 7.3 Dashboards in 2030

The growing interest in providing students with immediate and actionable feedback via dashboards is producing a number of innovative strategies for visualizing behavioral data as well as advanced data science techniques to understand the relationships between behavior and performance. The goal for the next ten years should not be to determine which dashboard is best, but rather to build both theory and design principles to provide students with effective feedback that is personalized to their needs and the context for their learning. In ten years, we should no longer be asking whether we should give students this kind of information, but rather have empirically-sound answers to questions about how dashboards can fulfill the promise of supporting learning for all students.

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