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Associations between learning analytics dashboard exposure and motivation and self-regulated learning

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ABSTRACT

Learning analytics dashboards (LADs) are intended to give relevant information to students and other stakeholders to inform potential next steps in the learning process. The current study examines the relationship between information indirectly presented through academic advisors' use of LADs, and college students' academic motivation, self-regulated learning, and academic achievement. We modeled how changes in student motivation and self-regulated learning (SRL) were related to what occurred during 1-on-1 meetings with academic advisors during which students had the potential to view representations of their achievement embedded within an Early Warning System (EWS) that visually represented aspects of their academic performance referenced with course averages. Constructs associated with SRL were moderated by advisor-advisee meetings. Results indicated that advisors' use of EWS while they met with students was negatively associated with the rate of decrease of students' reporting of using memorizing strategies but positively related when students' performance was compared to that of their peers. We discuss the moderating effects of students' exposure to visualizations of academic performance on their SRL strategies and academic motivation. This study points to the importance of monitoring the effects of information presented via EWS on motivation and SRL.

1. Introduction

Learning analytics dashboards (LADs) are designed to communicate insights about student learning and student performance within a learning context (e.g., Ahn, Campos, Hays, & DiGiacomo, 2019; Aljohani, Davis, & Ally, 2016; Bodily et al., 2018; Gutiérrez, Seipp, Ochoa, Chiluiza, De Laet & Verbert, 2020; Kim, Jo, & Park, 2016; Park & Jo, 2015). The type of information displayed by LADs, however, varies. Some LADs have displayed cognitive and behavioral process-oriented feedback (Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018), while others have displayed snapshots of student performance to educators (Amo, Alier, & Casany, 2018). Many LADs have shown students' course performance average relative to the performance of their peers (e.g., Park & Jo, 2015). Showing such comparative information to students raises concerns that doing so may have negative unintended consequences.

Students can be exposed to comparative information indirectly during meetings with their academic advisors, as advisors use LADs to retrieve the information designed to support their advising process. Advisors can thus use LADs before, after, or during meetings with students for brainstorming and guiding students so they are academically on track. Advisors can also use LADs before or after

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meeting with students to compile a semester plan for students, identify students at risk, and monitor students' academic progress (De Laet et al., 2020, Gutierrez et al., 2018). During meetings with students, advisors can use information visualizations, such as histograms or line graphs that display grades of students in a course, the grades of the peers, and class average information to discuss the academic performance of the student (De Laet et al., 2020; Millecamp & De Laet, 2018). Early work examining the motivational implications of students' indirect exposure to LADs designed for advisors demonstrated that such exposure to comparative information predicted a decrease in adaptive approaches to learning that stress understanding and improvement (Lonn, Aguilar, & Teasley, 2015). Other work has shown a negative association between comparative visualization use and the quantity of student posts within an online classroom setting (Beheshitha, Hatala, Gašević, & Joksimović, 2016). Students' graph comprehension may also play a role—low graph comprehension has been shown to be negatively associated with students' help-seeking strategies (Aguilar & Baek, 2019). Such relationships likely vary as a function of courses, students, and institutions where LADs are deployed. Consequently, it is important to discover potential relationships between student use—or exposure to—LADs and academic outcomes of interest.

Understanding how LADs embedded in early warning systems (EWS) relate to student outcomes is important because they often use academic achievement information from institutional learning management systems (LMS) to provide real-time academic progress to academic advisors, affording the opportunity to intervene when students are at risk for academic setbacks. Such interventions are predicated on the information provided, introducing the possibility of influencing student learning behaviors if students are exposed to comparative information that was not designed for their use. Early warning systems (EWS) are becoming commonplace in LMS's, and typically show the performance of individual students in relation to their classmates (see Aguilar, Lonn, & Teasley, 2014; Krumm, Waddington, Teasley, & Lonn, 2014; Lonn, Aguilar, & Teasley, 2013 for examples).

To date there has been limited work incorporating motivation and SRL research on LADs embedded within early warning systems. This is partially due to the imperative to first develop reliable predictive models of student performance that underpin recommendations or suggest a set of interventions. Ocumpaugh et al. (2015), for example, developed reports for guidance counselors using ASSISTMents College Prediction Model. Their EWS reported the likelihood of a student attending college and reported measures of engagement for specific groups of students. Such reports were intended to support guidance counselors in helping students set academic and career goals (Ocumpaugh et al., 2017). Relatedly, Jokhan, Sharma, and Singh (2018) used an EWS to predict student performance in an introductory university course and found that the EWS model was able to successfully identify underperforming students. Howard, Meehan, & Parnell (2018) and Dominguez, Bernacki, & Uesbeck (2016) have also found similar success in predicting student performance.

While it is important to focus on building reliable models for EWSs that predict students' academic outcomes, it is equally important to examine the relationship between the information LADs provide and students' self-regulation and motivation. Recent work in this area has investigated the effect of information presented in LMSs on learners' self-regulation. Beheshitha et al. (2016), for example, found that showing students visualizations of their performance in online discussions had mixed effects that varied based on their achievement goal orientation. Other work has examined student's sense-making of LADs and to what extent the impact of the information displayed on LADs was mediated by students' baseline self-regulation. Lim, Dawson, Joksimovic, and Gašević (2019) found that LADs had negative impact on learners overall because exposure to them induced social anxiety, especially when students were presented with how well their peers were doing compared to themselves.

What about indirect exposure, however? Is there a relationship between students' reported studying and self-regulation strategies, their motivation, and indirect exposure to LADs which display comparative information? (Such exposure could occur during advisee-advisor interactions where advisors use an EWS during counseling sessions.). The current study extends previous work by posing this question and examining how exposure to advisors' EWSs related to students' reported motivation and self-regulatory activity (e.g., Butler & Winne, 1995; Pintrich & de Groot, 1990; Wolters, 2004). The addition of self-regulation theory is an important contribution to the literature, given its association with key learning outcomes (Rheinberg, Vollmeyer, & Rollett, 1999; Schunk & Greene, 2018; Vighnarajah, Wong, & Bakar, 2009; Wolters, 1998), which can be influenced by what information is given to students, and when and how that information is delivered. We review the relevant motivation and self-regulation theory below.

1.1. Achievement Goal Theory

Achievement Goal Theory (AGT) is well suited to understand the potential motivational implications of LADs that display comparative information. Contemporary AGT proposes four goal orientations that describe students' reasons for accomplishing academic tasks and approaching the work associated with them. These orientations are mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance (Barron & Harackiewicz, 2001; Elliot, 2005; Elliot & McGregor, 2001; Elliot, Murayama, & Pekrun, 2011; Senko, Hulleman, & Harackiewicz, 2011).

Students with high mastery orientations focus on the development of understanding and improvement. In short, they 'learn for learning's sake' and reflect on how well they understand the material being taught to them (Elliot & McGregor, 2001). Mastery-oriented students have been shown to study information they find interesting over information that is actually tested (Senko & Miles, 2008), and have higher self-esteem when compared to peers high in performance-avoid goals (Shim, Ryan, & Cassady, 2012). By contrast, students who are high in performance-approach and performance-avoid orientations are motivated by comparisons to their peers. Those with performance-avoid orientation avoid tasks that threaten to show them as incompetent, whereas students with performance-approach orientations seek opportunities to publicly demonstrate competence (Elliot, 2005; Karabenick, 2004). Students with high performance-approach orientations have been shown to be more competitive and achieve at higher rates when compared to students high in mastery who were more interested in course material (Harackiewicz, Barron, Carter, Lehto, & Elliot, 1997; Midgley, Kaplan, & Middleton, 2001). Performance goals have also been linked to cheating behaviors (Tas & Tekkaya, 2010). Importantly, contextual factors can influence students' mastery and performance goals and beliefs (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002), and learning environments that are perceived as mastery oriented have been shown to support adaptive help-seeking behaviors in college students, while performance-avoid goals have been shown to relate to maladaptive help avoidance patterns (Karabenick, 2004).

While the differences between performance-avoid and performance-approach are well studied, Hulleman, Schrager, Bodmann, and Harackiewicz (2010) note there are differences in findings associated with both constructs that are likely the result of differences in measurement and methods. The Achievement Goals Questionnaire (AGQ; Elliot & McGregor, 2001), for example, measures performance based on normative comparisons (e.g., doing "better" than others), while the Patterns of Adaptive Learning Scale (PALS; Midgley et al., 2000, pp. 1–66) instead focuses on self-presentation components of performance (e.g., "showing" others that one is good at classwork) (Hulleman et al., 2010).

How performance information is displayed by a LAD may have different consequences depending on students' achievement goal orientations (Aguilar, 2018b). Those with higher mastery goal orientations may prefer self-focused information that provides feedback about changes in their own performance whereas those with performance goals should prefer information about how they compare to others. For example, Beheshita et al. (2016) found that students with mastery goal orientations produced greater performance on the writing posts after being exposed to visualization with information on the quality of their writing posts than after being exposed to visualization that compared their writing performance to class average.

Second, and potentially more important, is the possibility that visualizations to which students are exposed may alter their goal orientations. Mastery oriented students, for example, might become more performance-oriented if they are continuously exposed to comparative information through learning analytics applications. In other words, students initially focused on self-improvement and increased understanding may become more concerned with performance goals—their standing relative to others. It may also reinforce the performance focus of those already higher in performance goals. Recent work in this area suggests that this is case. Fleur, van den Bos, and Bredeweg (2020), for example, presented students with visualizations of comparative academic performance through a dashboard for 8-weeks and found that students who were given comparative information had increased "extrinsic motivation scores"—which are conceptually similar to performance orientation as conceptualized by AGT (e.g., "If I can, I want to get better grades in this class than most of the other students."). Results from this study also indicated that "intrinsic motivation," which was measured by items analogous to mastery orientation items (e.g., "The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.") decreased at the end of the 8 weeks. Notably, students in the treatment group who did not have access to the visualization information had both extrinsic and intrinsic motivation scores decrease. Findings from Fleur et al. (2020) suggest that students with both mastery and performance goal orientations became more focused with performance goal orientation after the continual exposure to comparative information. The ubiquitous display of comparative information may thus have wide motivational consequences and warrants further examination.

1.2. Self-regulated learning (SRL)

Self-regulated learning (SRL) is defined by a set of individual strategies that students undertake in order to learn. Students, for example, set personal learning goals, monitor their progress towards those goals, seek help when they do not meet those goals, and reflect on that learning to understand if the strategies they used to reach a particular goal were in fact useful (Pintrich, 2004; Zimmerman, 2000, 2008). One way students that self-regulate their studying, for example, is to monitor their achievement and study tactics so that they are well calibrated (Winne & Jamieson-Noel, 2002). An influential model of self-regulated learning is Zimmerman's (1989) socio-cognitive triadic model, whereby a learner's behavior is a product of their understanding of an environments response to their previous behaviors (such as a teachers encouragement or discouragement). Since its inception, research has shown that learners who set goals, monitor their progress, and use (effective) strategies to meet their goals are more likely to master content in the short term, and sustain their efforts to do so in the long term (; Zimmerman, 2013).

Recent work has examined how SRL can be supported in technology-rich learning environments through the use of scaffolds which are embedded in a given technology to support student learning in such environments (e.g., Poitras, Lajoie, Schunk, & Greene, 2018). This differs from reporting functions of LADs, which generally display pertinent academic information. Work in this area has shown differences in students' experience when given access to student-facing LADs, with many choosing not to engage with the dashboard at all, while others focus on grade distributions of their class—this is especially for lower achieving students (Kia, Teasley, Hatala, Karabenick, & Kay, 2020). A recent review by Viberg, Khalil, and Baars (2020) suggests that the intersection between SRL and learning analytics is understudied; this helps address this gap in the literature.

1.3. Current study

The current study examines whether or not indirect exposure to LADs through academic advisors is related to study strategies (e.g., memorizing, elaboration, etc.), effort, persistence, and/or student motivation. We contribute to the learning analytics literature on self-regulated learning (e.g., Govaerts, Duval, Verbert, & Pardo, 2012) and motivation (e.g., Lonn et al., 2014; Roll & Winne, 2015) by answering the following set of research questions:

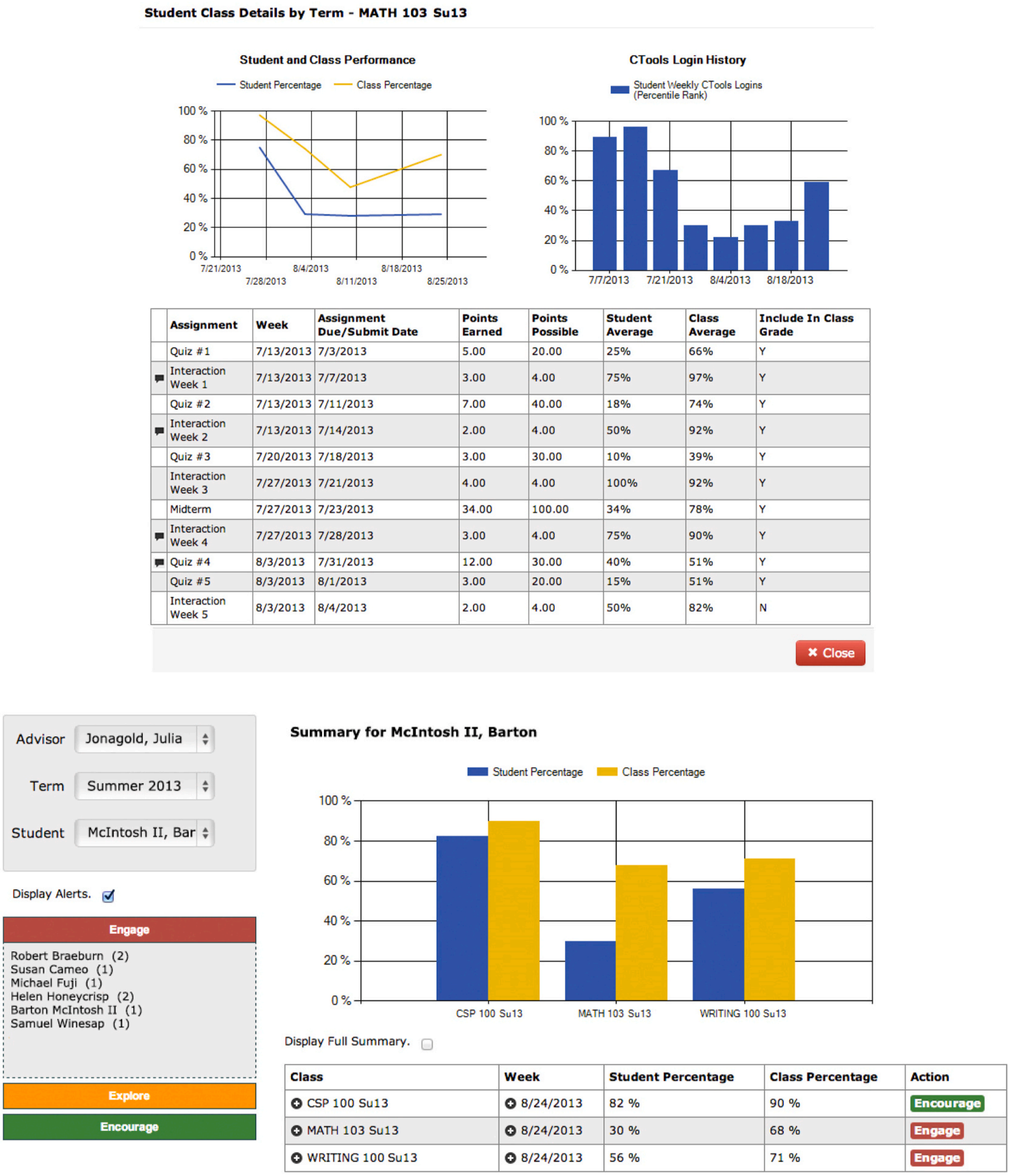
RQ1) Are changes to students' motivation and self-efficacy over the course of seven weeks related to advisee-advisor interactions, including the use of an EWS during meetings, after controlling for demographic characteristics and other factors?

RQ2) Are changes to students' SRL strategies over the course of seven weeks related to advisee-advisor interactions, including the use of an EWS during meetings, after controlling for demographic characteristics and other factors?

2. Method

2.1. Early warning system dashboard

The EWS used in this study was designed for use by academic advisors and draws its data from the learning management system (LMS) used by the institution. Fig. 1 shows two screenshots of the dashboard academic advisors had access to during a 7-week summer bridge program indented to provide extra support to students who had been identified as at-risk of struggling academically during their first year. (We note, however, that the interface of the EWS has since been extensively updated since the time of this study). Advisors were given assignment information for each of their students, as well as aggregate information that was used to compare individual students to the rest of the class. The visualizations used by the EWS focused on providing advisors information that enabled them to see whether or not their students were struggling (or succeeding) relative to their peers. We note that the dashboard only enabled comparisons with aggregate student performance, not comparisons with particular students. Previous work (i.e., Lonn et al., 2015) showed that this sort of comparative information was negatively associated with positive motivation orientations, such as mastery, so



Assignment	Week	Assignment Due/Submit Date	Points Earned	Points Possible	Student Average	Class Average	Include In Class Grade
Quiz #1	7/13/2013	7/3/2013	5.00	20.00	25%	66%	Y
Interaction Week 1	7/13/2013	7/7/2013	3.00	4.00	75%	97%	Y
Quiz #2	7/13/2013	7/11/2013	7.00	40.00	18%	74%	Y
Interaction Week 2	7/13/2013	7/14/2013	2.00	4.00	50%	92%	Y
Quiz #3	7/20/2013	7/18/2013	3.00	30.00	10%	39%	Y
Interaction Week 3	7/27/2013	7/21/2013	4.00	4.00	100%	92%	Y
Midterm	7/27/2013	7/23/2013	34.00	100.00	34%	78%	Y
Interaction Week 4	7/27/2013	7/28/2013	3.00	4.00	75%	90%	Y
Quiz #4	8/3/2013	7/31/2013	12.00	30.00	40%	51%	Y
Quiz #5	8/3/2013	8/1/2013	3.00	20.00	15%	51%	Y
Interaction Week 5	8/3/2013	8/4/2013	2.00	4.00	50%	82%	N

Class	Week	Student Percentage	Class Percentage	Action
CSP 100 Su13	8/24/2013	82 %	90 %	Encourage
MATH 103 Su13	8/24/2013	30 %	68 %	Engage
WRITING 100 Su13	8/24/2013	56 %	71 %	Engage

Fig. 1. Example of EWS Dashboard during time of use (Lonn et al., 2014).

advisors were instructed to not show comparative information to students.

2.2. Data sources

2.2.1. Demographic measures

Our sample consisted of 201 students enrolled in a summer bridge program for incoming freshman at a large research-intensive public university in the Midwest. The sample was 66% female, and 69% were members of under-represented minority groups. All students enrolled in the program were asked to complete a pre- and a post survey to measure motivation and self-regulated learning. Of the original sample, 176 (88%) completed both surveys.

2.2.2. Assessment of motivation and SRL

We used the Patterns of Adaptive Learning Scales (PALS) instrument (Midgley et al., 2000) to measure students' Achievement Goal orientations (see Barron & Harackiewicz, 2001), and detect any changes during the summer term. Achievement goal constructs include students' mastery, performance-approach, and performance-avoid goal orientations. Patterns of Adaptive Learning Scales (PALS) has been validated for use in various K-16 contexts (e.g., Abramovich, Schunn, & Higashi, 2013; Hulleman et al., 2010; Liem, Lau, & Nie, 2008; Linnenbrink-Garcia et al., 2012). Each item was measured on a 1–5 standard Likert scale (see Table 1 for descriptive statistics). Measured constructs include: *Mastery* (e.g., "One of my goals in class is to learn as much as I can"); *Performance-Approach* (e.g., "I want to do better than other students in my class"); and *Performance-Avoid* (e.g., "It's very important to me that I don't look stupid in my class.")

We used the Self-Regulated Learning Questionnaire (SRLQ) which was first developed for the international PISA studies (Artlet, Baumert, Julius-McElvany, & Peschar, 2000) and adapted by (Swalander & Taube, 2007). It is based on Zimmerman's (2000) SRL model. Measured constructs include: *Instrumental goals* (e.g., "I study to increase my job opportunities"); *Control expectation* (e.g., "If I want to learn something well, I can"); *Academic Self-concept* (e.g., "I'm good at most school subjects"); *Academic Self-efficacy* (e.g., "I'm confident I can understand the most complex material presented by the teacher"); *Effort and persistence* (e.g., "When studying, I keep working even if the material is difficult"); *Elaboration* (e.g., "When I study, I figure out how the information might be useful in the real world"); and *Memorizing* (e.g., "When I study, I try to memorize everything that might be covered").

2.2.3. Advisor-advisee meetings

Students met with their assigned academic advisers throughout the bridge program. Students took one of three courses: a math course, an English course, and a general study-skills course. All courses were mandatory for students. The English course and study skills course were identical. There were two levels of the math courses (intermediate algebra and mathematical reasoning). There were nine advisors total in the program who advised students. Advisors had access to the dashboard throughout the summer term, though we focus on access *during* meetings with students because such use was an anomaly and could be associated with changes in student motivation and self-regulation strategies. Students never had access to the dashboard, except through such anomalous advisor interactions.

We used EWS log files and logs taken from an advisor calendaring system to infer whether or not students were physically present while their advisor logged into the EWS. Timestamps in both log files were matched with meeting and EWS use, such that if an advisor was set to meet with a student from 12:30pm to 1:00pm, and they used the EWS at 12:35pm to view *that particular student's* profile, then a value of "1" would be generated to indicate that they used the EWS while the student was in the room. Thus, we were able to detect when a particular student was present as an advisor was viewing that students' information. Clerical staff recorded no-shows and cancelations, which were omitted from our analysis. Results from this matching process indicated that the EWS was used at least once while students were in the room for 22% of the students ($n = 44$). Eight students (3%) had two instances of this occurring, and one student had three.

At the end of the program, students were asked about particular meeting dynamics during 1-on-1 meetings using a 1–5 Likert-type

Table 1
Pre/post change of non-cognitive measures.

Motivation and SRL Measures	Pre-Survey	Post-Survey	Pre/post change	Alpha pre/post
Motivation & Self-Efficacy				
Mastery (PALS)	4.6 (.50)	4.5 (.57)	-.10*	.80/.85
Performance-Avoid (PALS)	2.7 (.92)	2.5 (.93)	-.20*	.82/.87
Performance-Approach (PALS)	2.6 (.95)	2.5 (.96)	-.10*	.83/.86
Instrumental Motivation (SRLQ)	4.1 (.70)	4.0 (.84)	-.10*	.78/.93
Academic Self-concept (SRLQ)	3.9 (.66)	3.6 (.72)	-.30***	.72/.83
Self-Efficacy (SRLQ)	3.8 (.64)	3.8 (.71)	*n.s.*	.78/.91
Control expectation (SRLQ)	4.0 (.61)	3.9 (.63)	-.10***	.74/.88
Self-Regulated Learning				
Effort and Persistence (SRLQ)	4.2 (.62)	4.0 (.73)	-.20***	.81/.90
Elaboration (SRLQ)	3.9 (.63)	3.9 (.69)	*n.s.*	.73/.90
Memorizing (SRLQ)	3.9 (.68)	3.6 (.84)	-.30***	.75/.90

Note: * = $p < .05$; ** = $p < .01$; *** = $p < .001$; We note that these changes, while statistically significant, are also quite small and range from a decrease of 0.10 to a decrease of 0.30 on a 1–5 scale. It is also worth noting that all changes, when present, were in the *negative* direction.

scale with "Never" and "Always" as anchors. Students were asked how often advisors made comparisons (i.e., compared to the class average, compared to other students, or if their performance between bridge courses was compared); whether or not advisors initiated discussions about their grades, LMS use, or performance status (i.e., green, yellow, or red). Students were also asked if learning analytics visualizations were referenced (with their answers dichotomized; yes = 1, no = 0).

2.3. Analytic strategy

First, we tested the reliability of our motivation measures (i.e., mastery, performance-approach, and performance-avoid) and SRL measures (i.e., academic self-concept, instrumental goals, control expectation, effort and persistence, and memorizing study strategies). All of the measures were reliable at pre and post, with alphas ranging from 0.74 to 0.93 (see Table 1 for pre/post means, standard deviations, and alpha values). Because we were primarily interested in whether or not these measures changed over 7-week summer period as a result of LAD exposure, we used paired-sample *t*-tests to determine any statistically significant changes in student motivation measure or SRL measures. Variables that had statistically significant changes were then modeled using multiple regression; we included motivation and SRL measures taken at pre as covariates, allowing us to model the rate of change in these constructs over a 7-week period. Motivation and SRL measures taken at the end of the 7-week period (post) were used as dependent variables. Reported meeting dynamics (described above) were used as covariates to control for student-reported advising behaviors that were distinct from actual LAD exposure. We also controlled for student demographic characteristics (e.g., gender, underrepresented minority status). This resulted in eight distinct regressions.

3. Results

We found lower post-test scores across all three motivational constructs, and all but two self-regulated learning constructs (see Table 1). Subsequent regression equations were specified to determine whether or not changes in motivation and self-regulated learning constructs were predicted by EWS use and/or exposure to visualizations within the EWS (RQ1 and RQ2), after controlling for relevant covariates. We thus model the rate of decrease in the models below, or the slope of the regression line for our dependent variables. The results below can be interpreted as modeling the *rate* of decrease in dependent measures; the larger the coefficients, the faster the rate of decrease as predicted by our independent variables (e.g., LAD exposure) after controlling for relevant covariates (e.g., underrepresented minority status).

3.1. Changes in student motivation (RQ1) and self-regulated learning strategies (RQ2)

Three multiple regression models were specified to model the rate of decrease in students' mastery, performance-approach, and performance avoid goal orientations (Table 2). Self-regulation items were included as covariates in the analysis, because motivation and self-regulated learning are processes that influence one another. We report standardized beta coefficients.

The degree to which students reported that their advisors compared them to other students was negatively associated with the rate

Table 2
Modeling linear change of students' motivation orientation (PALS).

	Motivation Measures (DV)					
	Mastery		Performance-Approach		Performance-Avoid	
	Β	(SE)	β	(SE)	β	(SE)
SRLQ						
Instrumental Motivation	.04	(.05)	-.13*	(.06)	.10	(.06)
Effort and Persistence	.18*	(.07)	.04	(.08)	-.06	(.07)
Academic Self-concept	-.01	(.06)	.02	(.07)	-.03	(.07)
Self-Efficacy	.01	(.09)	.15*	(.10)	-.11	(.1)
Control Expectation	.30**	(.10)	-.04	(.12)	-.04	(.11)
Advisor-Advisee Meetings						
LAD used during advising appointment	-.04	(.07)	-.10*	(.08)	.10*	(.07)
Compare performance in one course to another course	-.03	(.04)	-.03	(.05)	-.02	(.04)
Compare course performance to course average	.08	(.04)	-.09	(.05)	.12	(.05)
Compare academic progress to other students	-.19*	(.04)	.04	(.04)	.00	(.04)
Discuss individual assignment grades	.03	(.03)	.03	(.04)	-.05	(.04)
Discuss LMS login behavior	.07	(.03)	.03	(.04)	-.01	(.03)
Discuss E3 status	.03	(.04)	-.02	(.04)	.06	(.04)
Show EWS Screen	.03	(.09)	.08	(.11)	-.03	(.10)
Show graphs of academic progress	-.02	(.04)	.03	(.05)	-.08	(.04)
R^2	.44		.75		.77	

*Note:***p* < .05; ***p* < .01; ****p* < .001. Listwise deletion used for N = 169/210 Summer Bridge students with complete data. Coefficients reported are standardized betas, rounded to the nearest two decimal points. Variables entered into the model simultaneously. Each column represents a different regression model. The following covariates entered in the model but not shown: Female, Underrepresented Minority, Athlete, Mastery, Performance-approach, Performance-Avoid (pre and post).

of decrease in students' mastery orientation ($p < .05$). The number of instances where advisors used the EWS while they met with students was also negatively associated with the rate of decrease in students' performance-approach orientation ($p < .05$). Results also indicate an inverse relationship regarding the number of instances that advisors used the EWS while they met with students—the number of instances this occurred was positively associated with the rate of decrease in students' performance-avoid orientation ($p < .05$).

Five regression models were specified to model decreases in students' academic self-concept, instrumental goals, and control expectation (Table 3); as well as their reported effort and persistence, and memorization strategies (Table 4). Motivation items were included as covariates in the analysis, since motivation and self-regulated learning are processes that influence one another. We report standardized beta coefficients.

Results indicate that advisor-advisee interactions were generally not associated with decreases in students' self-regulation, with one key exception: The number of times that advisors used the EWS while they met with students was negatively associated with the rate of decrease in students' reported use of memorizing strategies ($p < .05$). Yet, if advisors compared performance in one course to another, there was a positive relationship ($p < .01$), indicating a *slower* rate of decrease.

4. Discussion

Our results support the conclusion that advisors' use of the EWS while students were in the session is important and is related to changes in motivation and SRL. Specifically, their use of the EWS while students were present was positively associated with the rate of decrease of students' performance-approach goal orientation. Because students' performance-approach orientation *decreased* on average, a positive association in this instance indicates that advisors use of the EWS is associated with an "acceleration" effect, i.e., the decrease in performance-approach orientation was likely to be greater for students who had advisors use the EWS while they were in the room. This is an important distinction, since performance-approach is the only performance construct that is associated with adaptive student outcomes (Senko et al., 2011). Thus, advisors who logged into the EWS and viewed a students' pages predicted students' becoming less performance-approach oriented over the course of Summer Bridge.

The opposite was true for students who wanted to avoid doing worse than their peers: negative changes in performance-avoid orientation were negatively associated with the rate of change of students' performance-avoid orientation. This can be interpreted as a "buffering," effect, indicating that advisors who logged into the EWS and viewed students' pages predicted students' slowing their loss of performance-avoid orientation. If we were to speculate, it is possible that advisors highlighted certain features that the EWS afforded, such as graphs showing comparisons between students. Recent work in this area (e.g., Kia et al., 2020) has shown that low achieving students in particular focus on grade distributions of their class. Yet, more work needs to be done to determine the impact of intermediaries use of dashboards when students are present.

What is clear, however, is that this inverse relationship speaks to the power of comparison for academically vulnerable students at an elite institution. Indeed, the only significant predictor of students' negative change in mastery orientation was the students' self-report that their advisor compared them to other students. As with students' change in performance-avoid orientation, our analysis indicates that advisors logging into the EWS and viewing students' pages was predictive of students' a kind of "buffering" relationship, i.e., advisors logging into the EWS was associated with their students slowing the decrease of the reported use of memorization strategies to learn.

Table 3
Modeling linear change of students' motivation and self-efficacy (SRLQ).

	SRL Measures (DV)					
	Academic Self-Concept		Instrumental Goals		Control Expectation	
	β	(SE)	β	(SE)	β	(SE)
PALS						
Mastery	.05	(.09)	-.01	(.11)	.19***	(.06)
Performance-Avoid	-.03	(.08)	.27*	(.10)	.00	(.05)
Performance-Approach	-.02	(.08)	-.24*	(.10)	-.05	(.05)
Advisor-Advisee Meetings						
LAD used during advising appointment	.00	(.08)	-.07	(.10)	-.09	(.05)
Compare performance in one course to another course	.03	(.05)	.14	(.06)	.05	(.03)
Compare course performance to course average	.02	(.05)	-.04	(.06)	-.06	(.03)
Compare academic progress to other students	.00	(.04)	.01	(.06)	.05	(.03)
Discuss individual assignment grades	.01	(.04)	.06	(.05)	.01	(.03)
Discuss LMS login behavior	.00	(.04)	.01	(.04)	.07	(.02)
Discuss E3 status	-.04	(.04)	-.05	(.06)	.06	(.03)
Show EWS Screen	.09	(.11)	-.11	(.14)	.08	(.07)
Show graphs of academic progress	-.08	(.05)	-.02	(.06)	-.11	(.03)
R^2	.54		.48		.75	

Note: *$p < .05$; **$p < .01$; ***$p < .001$. Listwise deletion used for N = 168/210 Summer Bridge students with complete data. Coefficients reported are standardized betas, rounded to the nearest two decimal points. Variables entered into the model simultaneously. Each column represents a different regression model. The following covariates entered in the model but not shown: Female, Underrepresented Minority, Athlete, Instrumental motivation, Effort and Persistence, Memorizing, Academic Self-concept, Control Expectation (pre and post).

Table 4
Modeling linear change of students' self-regulated learning.

	SRL Measures (DV)			
	Effort & Persistence		Memorizing	
	B	(SE)	B	(SE)
PALS				
Mastery	.18**	(.08)	.09	(.11)
Performance-Avoid	-.16	(.08)	-.01	(.10)
Performance-Approach	.07	(.08)	.20†	(.10)
Advisor-Advisee Meetings				
LAD used during advising appointment	.05	(.08)	-.14*	(.10)
Compare performance in one course to another course	.00	(.05)	.25**	(.06)
Compare course performance to course average	-.01	(.05)	-.03	(.06)
Compare academic progress to other students	-.03	(.04)	-.07	(.05)
Discuss individual assignment grades	-.04	(.04)	-.01	(.05)
Discuss LMS login behavior	.13	(.03)	.02	(.04)
Discuss E3 status	-.07	(.04)	-.14	(.06)
Show EWS Screen	.11	(.10)	-.13	(.14)
Show graphs of academic progress	.00	(.04)	.10	(.06)
R^2	.60		.60	

Note: *$p < .05$; **$p < .01$; ***$p < .001$. Listwise deletion used for N = 168/210 Summer Bridge students with complete data. Coefficients reported are standardized betas, rounded to the nearest two decimal points. Variables entered into the model simultaneously. Each column represents a different regression model. The following covariates entered in the model but not shown: Female, Underrepresented Minority, Athlete, Instrumental motivation, Effort and Persistence, Memorizing, Academic Self-concept, Control Expectation (pre and post).

With regard to self-regulated learning strategies, we note that self-reported memorization strategies were shown to decrease over the course of summer bridge. However, the rate of this decrease was also shown to be negatively associated with students who had advisors which logged into the EWS while they were in the room. As with students' motivation, this finding suggests a connection between more memorization strategies and advisors using the EWS while students were present, relative to students whose advisors did not use the EWS while students were present.

The literature on student academic motivation suggests that mastery approaches are generally positive, and lead to deeper learning (Barron & Harackiewicz, 2001; Cerasoli & Ford, 2014; Zimmerman & Dibenedetto, 2008), thus any reduction to those approaches warrants further investigation. Our study found a statistically significant decrease in students' mastery goals (i.e., learning for learning's sake) and performance goals (i.e., judging success or failure based on comparison to one's peers) for learning over the course of the summer bridge term. This result relates to the previous studies' findings that student motivation can decrease over a course and time (Bouffard, Marcoux, Vezeau, & Bordeleau, 2003; Darby, Longmire-Avital, Chenault, & Haglund, 2013; Opdenakker, Maulana, & den Brok, 2012; Otis, Grouzet, & Pelletier, 2005) and mastery goal orientation can decrease over time (Lazarides & Raufelder, 2017). Given this, students might benefit from learning analytics dashboards that promote mastery orientations as a means to mitigate against the general decrease of mastery orientation that occurred.

We note, however, that some students also benefit from having a performance-oriented approach to their learning (Midgley et al., 2001); thus, one might consider promoting performance in highly competitive institutional environments since performance-oriented students might be better equipped to adapt to a competitive environment. Students respond differently to different approaches such as some students might see that they are doing worse than their peers, get disappointed, and develop increased motivation to work harder whereas some students might suffer decreased motivation (Lim, Dawson, Joksimović, & Gasević, 2019). Therefore, it is important to attend to students' different goal orientation when presenting information to students (Aguilar, 2018a).

4.1. *Limitations*

Our findings speak to the potential influence of LADs on students' motivation and self-regulation via exposure to them in academic advising settings. However, we note that our standardized beta coefficients for the statistical analysis were low, but still meaningful given the indirect nature of LAD exposure. Also, our study is limited by the fact that advisors served as mediators for students' interactions with the EWS. While this was the intent of the EWS's design, it also limits our ability to infer direct effects of students' exposure to LADs presented in the EWS advisors used. Our study is also not a causal one—it is within reason that changes in student motivation and self-regulated learning strategies were an artifact of their experiences within the summer bridge program. Future research might consider testing for a causal relationship between LADs and student motivation and/or self-regulated learning through an experimental design—perhaps by manipulating the types of visualizations students are exposed to. Our findings, however, show that exposure to LADs by intermediaries is predictive of changes in motivation and SRL strategies over a relatively short period of time (seven weeks).

5. Conclusion

Our study suggests the importance of exploring the relationship between LADs and potential students' motivation and self-regulation strategies before learning analytics applications are implemented campus wide. Such studies would contribute to our understanding of whether or not certain visualizations displayed within LADs are associated with adaptive or maladaptive outcomes, and for whom. While there have been calls to incorporate psychometric data within learning analytics applications (e.g., Gray, McGuinness, Owende, & Carthy, 2014), there has been limited work to assess the potential influence a particular learning analytics application may have on non-cognitive factors. Motivation and self-regulation matters in all aspects of instructional contexts (e.g., Schunk, Meece, & Pintrich, 2014), and the learning analytics community would benefit from further study into how LADs can influence both processes.

This study is a step in that direction. Results show that even within a relatively short period of time (7 weeks) there can be changes in students' motivation and self-regulated learning. As LADs within learning analytics-based applications become more prominent, it is important to study how they can influence students' non-cognitive factors, especially their academic motivation to learn. Our study suggests that the influence is not unilateral, but rather may depend on the forms of representations educators, designers, and administrators choose.

Credit author statement

Stephen J. Aguilar: Conceptualization, Data curation, Methodology, Formal Analysis, Software, Supervision, Investigation, Writing- Original draft preparation. Stuart Karabenick: Writing- Review & Editing, Methodology. Stephanie Teasley: Resources, Writing- Review & Editing. Clare Baek: Writing- Review & Editing.

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