Journal of Research on Technology in Education

ISSN: 1539-1523 (Print) 1945-0818 (Online) Journal homepage: http://www.tandfonline.com/loi/ujrt20

Examining the Relationship Between Comparative and Self-Focused Academic Data Visualizations in At-Risk College Students' Academic Motivation

Stephen J. Aguilar

To cite this article: Stephen J. Aguilar (2017): Examining the Relationship Between Comparative and Self-Focused Academic Data Visualizations in At-Risk College Students' Academic Motivation, Journal of Research on Technology in Education, DOI: 10.1080/15391523.2017.1401498

To link to this article: https://doi.org/10.1080/15391523.2017.1401498

Published online: 11 Dec 2017.

JRTE | Vol. 0, No. 0, pp. 1–20 | © 2017 ISTE | iste.org/jrte
DOI: 10.1080/15391523.2017.1401498

Examining the Relationship Between Comparative and Self-Focused Academic Data Visualizations in At-Risk College Students' Academic Motivation

Stephen J. Aguilar
University of Southern California

Abstract

This qualitative study focuses on capturing students' understanding two visualizations often utilized by learning analytics-based educational technologies: bar graphs, and line graphs. It is framed by Achievement Goal Theory—a prominent theory of students' academic motivation—and utilizes interviews (n = 60) to investigate how students at risk of college failure interpret visualizations of their potential academic achievement. Findings suggest that visualizations only containing information about students themselves (i.e., self-focused affordances) evoked statements centered on mastering material. Visualizations containing information about students and a class average (i.e., comparative information), on the other hand, evoked responses that disheartened students and/or made them feel accountable to do better. Findings from this study suggest the following guidelines for designing visualizations for learning analytics-based educational technologies: (1) Never assume that more information is better; (2) anticipate and mitigate against potential misinterpretations—or harmful alternative interpretations—of visualizations; and (3) always suggest a way for students to improve. These guidelines help mitigate against potential unintended consequences to motivation introduced by visualizations used in learning analytics-based educational technologies. (Keywords: motivation, visualizations, learning analytics, Achievement Goal Theory, college students, educational technologies)

Spurred on by the growth of data analytics technologies designed to detect, predict, and/or improve on student learning, students are increasingly being presented with their academic performance information through learning technologies. Learning analytics-based educational technologies are one such class of technology; they utilize data analytics to analyze learning data wherever they are found, and communicate the resulting insights through a set of representations (Clow, 2013). The field has focused heavily on the development of quantitative techniques—and the application of those techniques—to detect patterns in data found in various educational settings (e.g., Elbadrawy, Studham, & Karypis, 2015; Harrison, Villano, Lynch, & Chen, 2015; Miller et al., 2015). Less attention, however, has been paid to how data-driven insights are represented to various stakeholders, and the effects of those representations on educational processes. While there has been some interest studying representations in the form of data visualizations (Duval, 2011; Santos, Govaerts, Verbert, & Duval, 2012; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013), only limited work has focused on better understanding how visualizations of learning data affect learning and student motivation.

Visualizations of learning data are often implemented via dashboards (e.g., Diana et al., 2017; Verbert et al., 2013; West, 2012) and seen by various stakeholders, but unlike more ubiquitous representations of academic information (e.g., letter grades), there is no clear precedent for their interpretation and design. It is necessary to address this gap in the research, since errors, bias, misunderstandings,

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/ujrt.

and/or misinterpretation of visualizations used by learning analytics-based educational technologies can result in communicating information that is potentially misleading or that contains unintended messages. When this occurs, the entire purpose of learning analytics may be undermined.

How various stakeholders make sense of visualizations is especially important when the stakeholders are students themselves. If a given visualization, for example, communicates "actionable" information to students—that is, information that suggests students act in a certain manner—then it is important to demonstrate the efficacy of that information before exposing students to it. This is particularly important when it comes to student populations that are susceptible to messages that may interfere with their learning processes, such as first-generation college students (Tinto, 1975; 1987) and minority students who have been shown to be susceptible to negative comparisons, as is the case with stereotype threat (Steele, 1997; Steele & Aronson, 1995).

This study examines the relationship between visualizations and academic motivation—an important factor for student leaning and engagement (Berger & Karabenick, 2011; Pintrich & de Groot, 1990; Rheinberg, Vollmeyer, & Rollett, 1999; Schunk, Pintrich, & Meece, 1996). It focuses primarily on how students interpret visualizations in the form of line graphs depicting academic achievement over time, and is framed by Achievement Goal Theory (Elliot, 2005; Elliot & McGregor, 2001).

Achievement Goal Theory

Achievement Goal Theory (AGT) (Barron & Harackiewicz, 2001; Elliot & McGregor, 2001; Elliot, Murayama, & Pekrun, 2011) is a framework for understanding the motivational constructs that relate to adaptive and maladaptive ways in which students can engage with their learning environment. AGT states that students set various goals within a learning environment based on their orientation toward the value of achievement and their perceived level of competence. Contemporary AGT has been structured to include four goal orientations that describe students' motivation for accomplishing academic tasks and approaching the work associated with them. These orientations are "mastery-approach," "mastery-avoid," "performance-approach," and "performance-avoid" (Elliot & McGregor, 2001). This study uses AGT as a framework for understanding the technology-mediated information environment created when students attend to visualizations of their academic performance within a learning analytics application. It is posited that, as with other learning environments, AGT provides a useful theoretical frame to investigate how students interpret visualizations.

Students with high mastery-approach orientations focus on external standards that are imposed by the task (e.g., being able to correctly solve for x in an equation). High mastery beliefs have been shown to support deeper processing and more meaningful self-regulated learning (Meece, Blumenfeld, & Hoyle, 1988). Mastery-oriented students have also 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 orientations (Shim, Ryan, & Cassady, 2012).

Students who are high in performance-approach and performance-avoid orientations are motivated by comparisons to their peers. Students with a performance-avoid orientation are hesitant to undertake tasks that threaten to show them as incompetent, sometimes choosing to avoid them altogether. Conversely, students with performance-approach orientations seek opportunities to publicly demonstrate competence (Elliot & McGregor, 2001). 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). High performance-avoid beliefs, in contrast, have been linked to superficial learning strategies and cheating behaviors (Elliott & Dweck, 1988).

Importantly, contextual factors can influence students' mastery and performance goals and beliefs (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002); learning environments that are perceived as mastery oriented have been shown to support adaptive help-seeking behaviors in college students, while performance-avoid environments been shown to relate to maladaptive help-avoid patterns (Karabenick, 2004). Recent work has also explored whether or not achievement goal constructs measured at the student-level can be also be attributed to features of students' classroom environments, suggesting that such a link may exist (Lam, Ruzek, Schenke, Conley, & Karabenick, 2015). This is important, as it implies that the learning context may have a large role to play in how students orient themselves toward their work—further suggesting that changes in said environment can intervene. In this light, learning analytics-based educational technologies provide an additional environment that students are exposed to.

Visualizations in Learning Analytics-Based Educational Technologies

Graphs are often chosen as visualizations in learning analytics-based educational technologies (e.g., Krumm, Waddington, Teasley, & Lonn, 2014; Lonn, Aguilar, & Teasley, 2014; Scheffel, Drachsler, Kreijns, de Kraker, & Specht, 2017). Meyer, Shamo, and Gopher (1999) showed that graphs are effective means of presenting information, as long as the information they present is nonrandom and well structured. The literature on graph comprehension suggests that different types of graphs (e.g., bar graphs, lines graphs, pie charts) contain features that afford different interpretations. Students who view line graphs, for example, have been found to be more likely to describe *x–y* relationships, whereas students who were given bar graphs were more likely to interpret key differences between two variables, that is, main effects (Shah & Freedman, 2009).

Line graphs in particular are the second most common visualization utilized by learning analytics-based educational technologies (Bodily & Verbert, 2017). Line graphs generally depict linear relationships between two or more variables (Shah & Carpenter, 1995), and are well suited to communicating information that is "discrete." Each line represents a unique piece of information (e.g., a student's information vs. aggregate information), and do so in a way that implies trends (i.e., the slope of the line). Line graphs also facilitate quicker judgments of change when compared to bar graphs (Hollands & Spence, 1992).

This study extends previous work with an early warning system (EWS) primarily used by academic advisers (Krumm et al., 2014). The online system aggregates students' online grade-book data, and presents those data to advisors though a graphical user interface that utilizes both line graphs and bar graphs to visualize student achievement (Figure 1; for details on how it was implemented in a large university setting see Lonn Aguilar, & Teasley, 2013).

Despite not being a student-facing system, research has demonstrated a relationship between students' exposure to the tool itself and their academic motivation, suggesting the possibility that exposure to visualizations of academic performance may lead to an acceleration in students' already decreasing mastery orientation, as conceptualized by AGT (Lonn et al., 2014). The study by Lonn et al. (2014) was the first to frame the study of a learning analytics application with motivation theory. The current study extends this work by zeroing in on students' interpretations of lines graphs, both because of their ubiquity in learning analytics-based educational technologies, and because of their suggested relationship to student motivation.

Research Questions

This study focuses on the potential motivational affordances of line graphs that depict academic information, and addresses the following research questions:

RQ1) When asked to think about their performance at the midpoint in a hypothetical course, how do college students identified as at risk of facing academic challenges make sense of five different line graphs depicting various academic scenarios?

RQ2) When comparing graphs with similar trends to one another, but different affordances/design elements, which graphs do students choose as "more motivating," and how do they explain their reasons for their decision?

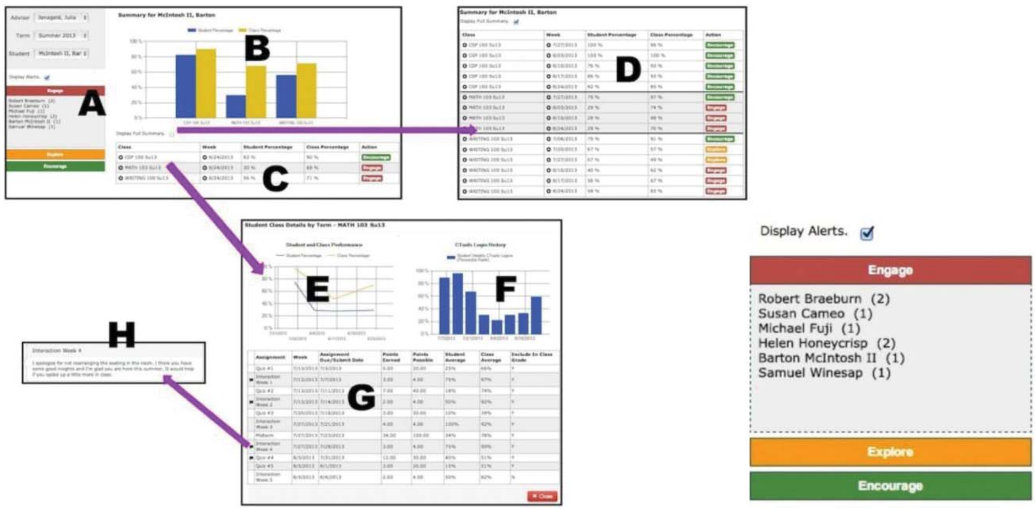

Figure 1. EWS dashboard (Lonn, Aguilar, & Teasley, 2014).

RQ3) How do students predict their future performance using graphs with similar trends to one another, but different affordances/design elements?

Method

This study used semistructured interviews to capture the ways college students at risk of academic challenges interpret graphs designed to communicate academic performance. Semistructured interviews are narrower than unstructured interviews (which mimic natural conversations), but less rigid than structured interviews, which prevent the interviewer from deviating from a set script (Cousin, 2009). This enabled the interview protocol to focus on sense-making as it relates to student motivation, and also enabled the development of an a priori coding scheme framed by AGT. The semistructured interviews were organized into five sections: (1) academic self-concept and graph affinity; (2) sense-making across scenarios; (3) identifying graphs that motivate; (4) completing graph trend lines; and (5) graph information evaluation. The materials, procedure, coding scheme, and participants are described next.

Participants

Students who participated in this study were drawn from the summer bridge program at a large Midwestern university designed to support students are at risk of facing additional academic challenges. Students were recruited in partnership with staff members who administer the summer bridge program every summer. Summer bridge cohorts are typically 200–250 students. Various criteria are used to identify students who participate in summer bridge, including:

- First-generation college status.
- Students who come from low socioeconomic backgrounds.
- Students who attended low-performing high schools.
- Students who attended large urban schools.
- Students who attended small rural schools.
- Students who are underrepresented in the academy.
- Students who have overcome “great life circumstances.”
- Students who have been referred by other students or other students or staff.

Recruitment

E-mail addresses from the 2013 ($n = 217$), 2014 ($n = 201$), and 2015 ($n = 233$) summer bridge cohorts were provided by program administrators. At the time of the study, the 2013 cohort were primarily sophomores, the 2014 cohort were primarily freshman, and the 2015 cohort were recently matriculated students—that is, the summer bridge program was their first official term in college. Participants in the study were recruited during two periods: once during the winter 2015 term, and once during the summer 2015 term. During each recruitment period, students were sent an e-mail asking them to participate in the study, and were offered a $20 honorarium for their participation. Students were told that their participation would help "improve both the summer bridge program and the learning technologies that future students will use at this university." Students were chosen to participate in the study on a first-come, first-served basis, and according to mutually overlapping schedules.

Data Sources

There are two primary sources of data for this study: (1) demographic and academic information obtained from the institution's data warehouse for all three summer bridge cohorts, and (2) recorded and transcribed interviews of study participants ($n = 60$).

Demographic and academic variables. Students' academic and demographic data were obtained via the university's data warehouse. These data include high school grade-point average (GPA), ACT composite score, gender, and underrepresented minority status, and were obtained for every student who was eligible to participate in the study (i.e., the 2013, 2014, and 2015 summer bridge cohorts).

Semistructured interviews. Interviews were conducted in two waves. Wave 1 consisted of 30 students drawn from across the 2013 and 2014 cohorts. These students were summer bridge alumni, having completed the program during previous summers. Wave 2 consisted of 30 students who were recruited from the summer 2015 cohort. These students were interviewed while the summer bridge program was underway. The interviews lasted anywhere from 10 to 40 minutes, and were recorded and transcribed ($M_{\text{minutes}} = 25$, $SD = 5.2$).

Final Sample

The final sample for the study consisted of 18 males and 42 females ($n = 60$), with half consisting of students from the 2013 and 2014 cohorts, and the other half consisting of students from the 2015 cohort. The data are consistent with summer bridge norms, which typically serve twice as many females as males. Students interviewed, however, do not represent the larger Midwestern university student community. See Table 1 for summary statistics of sample participants.

Table 1. Demographic variable descriptive statistics

Demographic	*N* total	*N* wave 1	*N* wave 2	Proportion
Race/ethnicity				
White	7	5	2	.12
Hispanic/Latino	11	6	5	.18
Black/African-American	36	16	20	.60
Asian/Pacific Islander	3	2	1	.05
Two or more	2	1	1	.03
Gender				
Male	18	10	10	.33
Female	42	20	20	.67
	M	*Wave 1 M*	*Wave 2 M*	
Academic performance				
ACT composite	22.95	22.80	23.10	
High school GPA	3.55	3.56	3.53	

Materials

Line graphs were chosen due to the high likelihood of their use in learning analytics-based educational technologies (Bodily & Verbert, 2017). They are a popular choice, in part, because they present linear relationships between two or more variables over time (Shah & Carpenter, 1995). They are also well suited to study students' sense-making of graphs that show self-focused information (e.g., Figure 2, Graphs 1a and 2a) and comparative information (e.g., Figure 2, Graphs 1b, 2b, and 2c) over the course of an academic term. Comparative and self-focused design features map onto Achievement Goal Theory (Elliot & McGregor, 2001), which posits similar dimensions: mastery (individual) and performance (comparative). Line graphs are also best suited to communicate information that is "discrete," and facilitate quicker judgments of change when compared to bar graphs because each line represents a unique source of information (Hollands & Spence, 1992). The graphs used for this study rely on these two factors: they depict academic performance over time, and three of the graphs contain two lines, each depicting a discrete piece of information. Students were asked to examine five line graphs that depicted their academic performance in a hypothetical course of their choosing.

Graphs were presented on a computer screen for the majority of the interview, though paper versions were used for the grade prediction task (RQ3). Each graph depicted the midway point of a 14-week academic term (the typical length of a term at this university). Graphs were designed along two dimensions: the direction of the trend (upward or downward), and whether or not they depicted self-focused or comparative information.

Upward Trending Graphs

There were two types of upward-trending graphs. Graph 1a consisted of one line that represented a student's progress in a hypothetical 14-week course, and was designed to afford information consistent with a mastery orientation posited by AGT (i.e., only a student's information is depicted, making performance comparisons to other students unlikely). Graph 1b consisted of the same individual performance line and a line depicting the class average. This graph was designed to afford comparative information that is relevant for AGT's performance-avoid or performance-approach orientations that focus on students' performance relative to the performance of others (Figure 2). Both upward-trending graphs depicted a trend that began at 50% proficiency in course material (i.e., relatively poor performance) but steadily grew, reaching 73% by the midpoint of the term. The class average line present in Graph 1b, while perfectly parallel to a student's performance line, was always 5% points higher (i.e., if the individual line showed 73% by week 14, then the class average line showed 78%).

Downward Trending Graphs

There were three downward-trending graphs: Graph 2a, Graph 2b, and Graph 2c. As with upward-trending graphs, one was designed as self-focused (Graph 2a), which is consistent with mastery in AGT. Graphs 2b and 2c were designed to have performance affordances, and included a class average line. The downward trending graphs visualized a trend that rose for the first 5 weeks, then

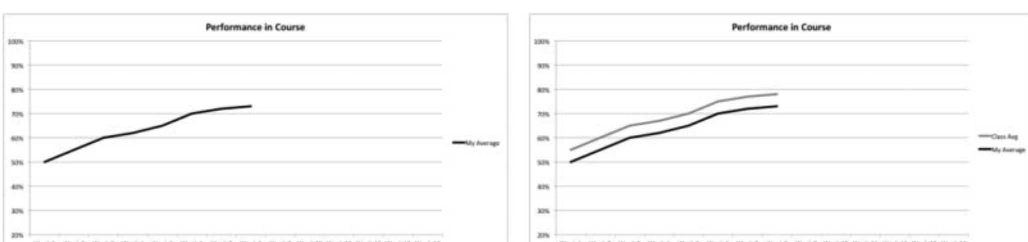

Figure 2. Graph 1a, self-focused (left), and graph 1b, comparative (right).

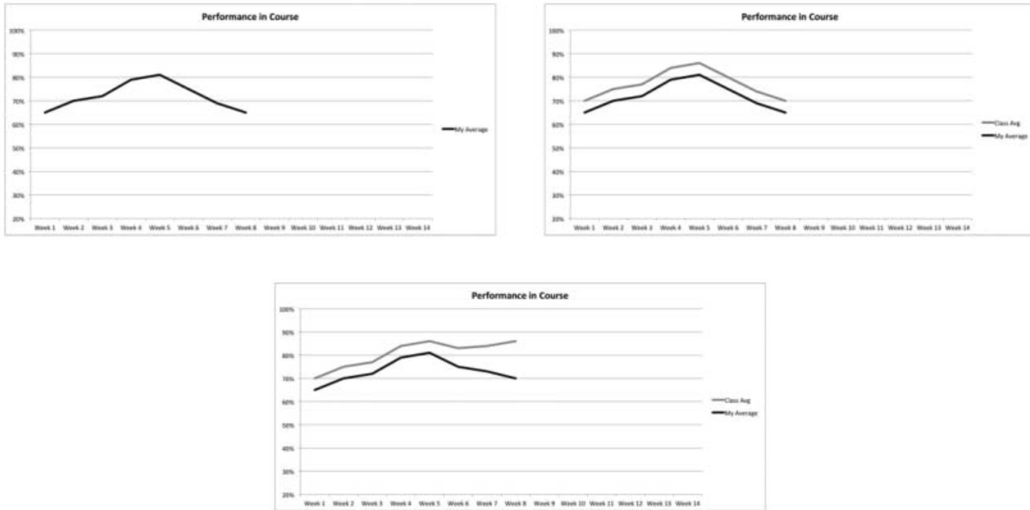

Figure 3. Graph 2a, individual (left), graph 2b, comparative (right), and graph 2c, divergent (bottom).

steadily declined to a low of 65% by week 8. As with the upward-trending graphs, the first graph (2a) depicted a student's individual performance, while the second graph (2b) depicted the student's performance as well as the average performance of the class (Figure 3). The class average line was also perfectly parallel to a students' performance line, but positioned to always be 5% points higher. The third graph in this series was similar to the comparative graph (2b); however, rather than remain parallel, the class average noticeably diverged from the student's individual average during week 6 of the term.

Procedure

At the start of each semistructured interview, students were briefed on the purpose of the study and were asked for their consent to be recorded. Interviews were organized into five sections: (1) academic self-concept and graph affinity; (2) sense-making across scenarios; (3) identifying graphs that motivate; (4) completing graph trend lines; and (5) graph information evaluation. Each section was designed to contextualize and capture the sense-making activities of students as they examined line graphs depicting academic performance. (Sections 1 and 5 were transcribed but not included in this analysis due to their departure from the focus of the main study).

Sense-Making Across Scenarios (RQ1)

Section 2 of the interview began by asking students to consider a hypothetical course they would likely take in the future, and to keep it in mind while they examined subsequent lines graphs. Students' choices contextualized the interview but were not analyzed. Students in wave 2 were also asked what would motivate them to accomplish their stated goals. This question was added after analyzing wave 1 transcripts; it was included to provide additional context to students' subsequent answers. Once a course was chosen, students were presented with graphs depicting their performance in that course.

Students were prompted to think about a hypothetical course for two reasons. First, it enabled the interviews to stay consistent across waves. Students from wave 1 did not have any direct experience with college courses, so it would have been impossible to show them data from courses that they had previously taken in college. Second, this study is agnostic with respect to the source of the academic information used to construct visualizations of academic information. Consequently, it was important to give students the autonomy to pick courses on their own, because this would ensure that their responses would be contextualized in a manner that would resonate with their own experiences as students. As the results show, students picked a variety of courses for a variety of reasons, which allows for the results to speak to more than one academic domain. Students chose courses ranging from math courses to courses in the humanities. Figure 4 provides an overview of the courses chosen, with the taller bar indicating the number of students who chose a course in a given field, and the shorter bar representing different courses within that field; 12 students, for example, chose a science course, and four different types of science courses were chosen (biology, chemistry, etc.). Once students had a course in mind and explained their reasons for choosing it, they were presented with the first of five graphs to examine.

Students were given approximately 1 minute to examine each graph before any questions were asked, and were instructed to signal the interviewer once they were ready to answer questions. Graphs depicting individual information were always shown first, since pilot testing determined that it was impossible for students to “un-see” comparative information once it was presented; graphs were presented in one of two potential orders. The first began with upward-trending line graphs, and the second began with downward-tending line graphs.

Half of the students interviewed ($n = 30$) were presented with graphs in the first order, and the other half ($n = 30$) were presented with graphs in the second order. The two orders were chosen to ensure that half of students began the interview by seeing graphs depicting a downward (i.e., academically pessimistic) trajectory, and the other half of the students began the interview by seeing graphs depicting an upward (i.e., academically optimistic) trajectory. Students were asked questions intended to capture sense-making around the following five dimensions:

Comprehension. Students were first asked to use the graph to determine “how they were doing” in the course. The phrase was purposefully agnostic about correct/incorrect answers, and allowed for students to give a broad range of responses. This, in turn, enabled the capture of any sense-making the students communicated; students could, for example, simply say “badly.” Follow-up questions allowed for students’ answers to be tied to any graph feature they focused on in their explanation. For comparative graphs, students were also asked to determine how other students (represented by the class average line) were doing in the course.

Salient features. Students were asked to reflect on the parts of the graph they found salient. This was operationalized as what students stated they noticed first. The follow-up question asked students to anchor their answer to specific graph features, or anything else that they felt made their started feature noticeable.

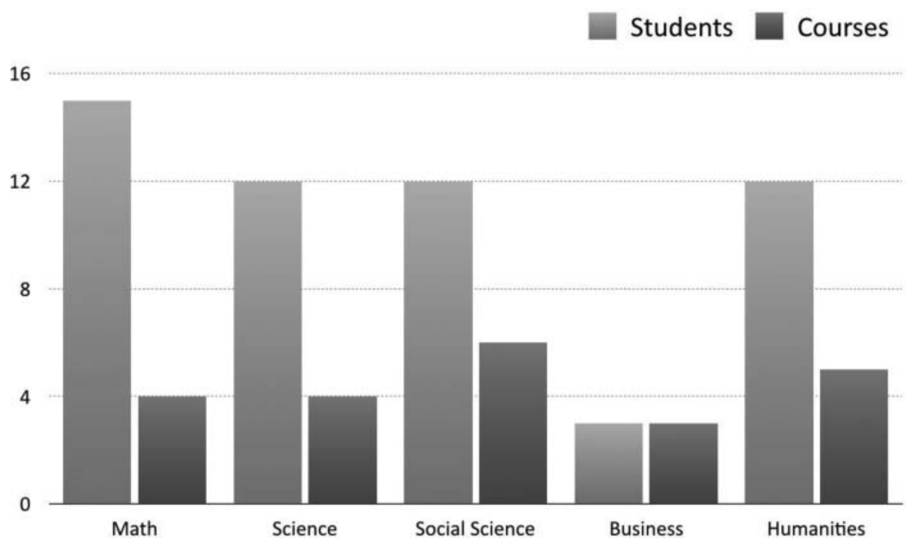

Figure 4. Students’ course selection, and number of courses within that field.

Communicating graph information. Students were asked to state how they would explain their performance as depicted by the graph to one of their peers. If students dissociated themselves from the information that the graph depicted, perhaps by answering in generic terms (e.g., "I would tell them that this graph shows how they're doing from week 1 to week 8"), then they were reminded that the information was about them. The clarifying question, then, served to remind them of the hypothetical course they would likely take in the future.

Identifying Graphs That Motivate (RQ2)

After students answered questions for each of the upward- or downward-trending graphs, they were asked to choose a graph from the set that they believed would make them "more motivated to do well in the course." Students did this twice, once per set (upward-trending and downward-trending). Students were given 1–2 minutes reexamine each of the graphs before they chose the one they felt would motivate them more. Once they selected it, they were asked to explain their choice.

Completing Graph Trend Lines (RQ3)

Since each of the graphs depicted a course at its midpoint, students were asked to predict their future performance in the course by completing the graph using a pen that was provided. Students were asked to explain their reasoning behind their predictions.

Coding Scheme

An a priori coding scheme was developed using the major constructs posited by Achievement Goal Theory (Elliot, 2005; AGT, Elliot & McGregor, 2001). This enabled the deductive coding of interview transcripts; each construct (e.g., mastery) was assigned a code. In accordance with AGT, three major codes were developed that paralleled the AGT constructs of: mastery, performance-approach, and performance-avoid. The language students used while examining the graphs and answering questions was compared against the Patterns of Adaptive Learning (PALS; Midgley et al., 2000).

In accordance with AGT, and examples taken from the PALS survey, statements coded as "mastery" were characterized by inward-focused language that typically spoke of learning "more" over time (e.g., "I started to learn more after a while"). (Mastery statements never included comparative statements.) Statements where students compared themselves to peers in order to outperform them were coded as performance-approach statements, whereas statements where students compared themselves to peers in order to avoid doing "worse" than them were coded as performance-avoid. The code of "performance" was added after analysis indicated that many responses had a clear comparative dimension, but did not take the further step of indicating whether or not it was important to avoid incompetence (performance-avoid), or demonstrate competence (performance-approach).

Codes were applied by one rater to interview sections 2 through 4, which capture students' sense-making of graphs (RQ1), identification of more motivating graphs (RQ2), and completion of graph trend lines (RQ3). Where appropriate, multiple codes were applied to overlapping segments of students' responses. The coding scheme is summarized in Table 2.

Table 2. Coding scheme

Construct	PALS example	Interview example
Mastery	"It's important to me that I learn a lot of new concepts this year."	"At the beginning, I didn't know much, but I started to really learn more . . ."
Performance	n/a*	"First thing I noticed was that my average was the same, and then I looked up and saw that the class average was a bit higher."
Performance-approach	"It's important to me that I look smart compared to others in my class"	"I'm comparing myself to other students and I would wanna be part of the class average on the higher end."
Performance-avoid	"It's important to me that I don't look stupid in class"	". . . it sucks being the one person that's . . . I guess not the one person but not progressing, or increasing as everyone else is"

*Performance example not available in PALS survey instrument.

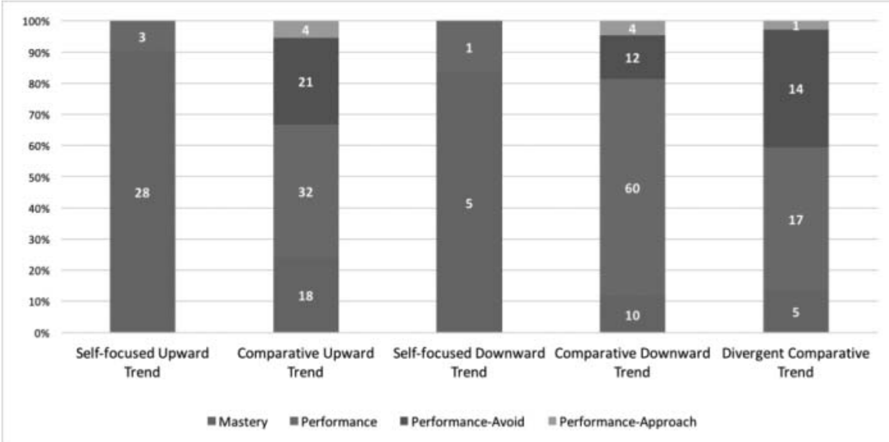

Figure 5. Overview of AGT codes across comprehension, salience, and communicating graph information interpretations.

Results

Results are organized by research questions. The first section presents the results of students' sense-making, which consisted of (1) students' comprehension of the five graphs used, (2) how students would communicate the affordances of the graph to their peers, and (3) the salient features they noticed within each graph. The second section presents the results of which graphs students found more motivating and why. The third section presents the results of students' predictions of their future performance in the hypothetical course.

Sense-Making Across Scenarios (RQ1)

Figure 5 aggregates the AGT codes across students' comprehension of the graph, how they would communicate graph information to others, and what they found most salient. Each code is represented as a proportion of total codes deduced within transcript segments. For example, overall the self-focused graph was interpreted to have mastery affordances 28 times (approximately 90% of the time), and performance affordances 3 times (approximately 10% of the time). Overall, graphs that were self-focused were more likely to elicit mastery statements from students. Graphs with comparative statements elicited statements that were coded along every AGT dimension (i.e., mastery, performance-avoid, performance-approach, and performance).

Comprehension

The self-focused graphs yielded more mastery statements (Figure 6), which one would expect given that mastery is an inward-looking construct; the graph design does not show any comparative information. Comparative graphs yielded similar results—students' interpretations of comparative graphs yielded more codes within the performance, performance-approach, and performance-avoid coding family. Of these, general performance (i.e., neither approach nor avoid) statements were made more often, potentially indicating that students did interpret performance aspects of the graph. Performance-approach, however, is absent from all but one graph type (2a, comparative upward), which yielded one code. This suggests that performance-avoid has the potential to be more likely to be interpreted when a graph shows a comparison.

Communicating Graph Information

Self-focused graphs yielded more explanations that parallel mastery language when presented with self-focused graphs, and more performance explanations when presented with comparative graphs.

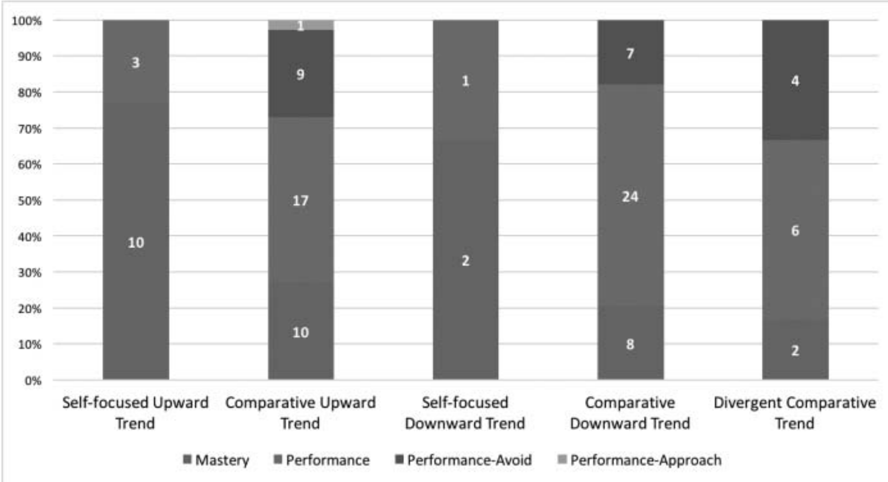

Figure 6. Overview of AGT coded segments as students answered: “How are you doing in the course?”

Comparative upward-trending graphs and divergent graphs were interpreted through multiple motivational lenses (e.g., mastery, performance, performance-avoid, etc.). Students’ interpretations of comparative downward-trending graphs were more often coded with nondimensional performance (Figure 7).

Salient Features

Students used mastery language when they commented on the most salient features of the self-focused graphs they were presented. This suggests that noncomparative (i.e., self-focused) line graphs afford interpretations in line with AGT’s mastery construct. The same is true for comparative graphs, which yielded a collection of statements that were coded as performance, performance-avoid, or performance-approach. The comparative downward trend and the divergent trending graphs are important to highlight; they yielded more performance-avoid statements than other types of performance statements, indicating that students were attuned to doing worse compared to their peers (Figure 8).

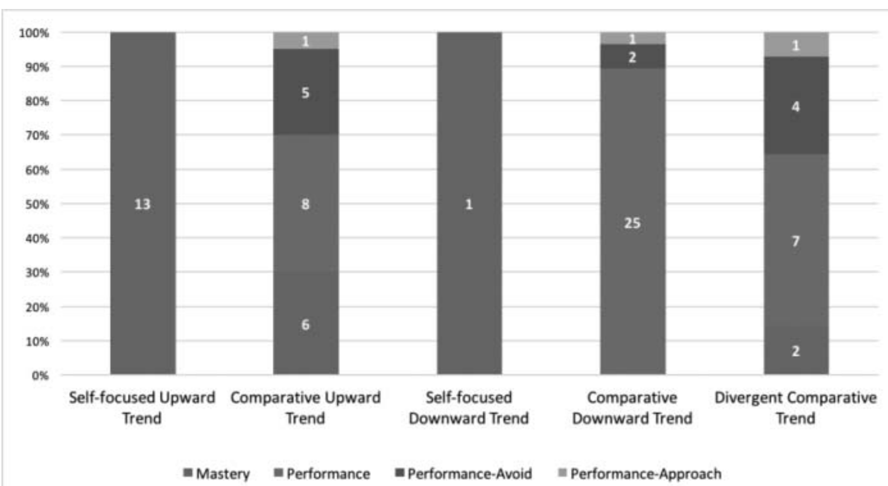

Figure 7. Overview of AGT coded segments as students answered: “How would you explain this graph to one of your fellow students/peers?”

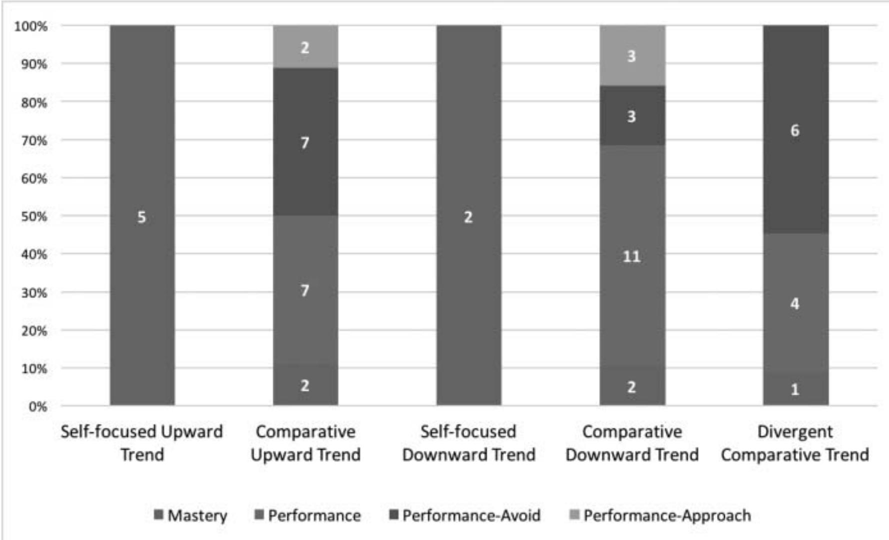

Figure 8. Overview of AGT coded segments as students answered: "What was the first thing you noticed about the graph?"

Identifying Graphs That Motivate (RQ2)

When students were asked to choose between the self-focused upward-trending graph and the comparative downward-trending graph, 22% ($n = 13$) chose the former, while the majority (78%, $n = 46$), chose the latter. One student did not make a choice. When students were asked to choose between the three downward-trending graphs, the majority of students chose the divergent graph as the most motivating (67%, $n = 40$). The comparative graph was the second most popular choice (22%, $n = 13$), and the self-focused graph was chosen least often (12%, $n = 7$). In total, 162 codes were applied to students' reasons for choosing the most motivating graph using the AGT coding scheme. Figure 9 provides an overview of reasons students gave for their choices. Performance-avoid was the most dominant motivationally interpretive modality for students as they made their choice, which indicated that students were most motivated by not wanting to be behind (i.e., demonstrate incompetence), in comparison to their hypothetical peers.

Students were asked to draw the rest of their performance line through week 14 for each graph in order to demonstrate how they thought they would perform through the end of the course. The endpoints of the drawn lines were then examined and linked to numerical values (e.g., a line ending at the very top of the graph by week 14 would be coded 100%, indicating that a student believed he or she would earn the best possible grade in the course). As students drew the trend line, they explained their reasons for drawing their particular line. Their responses then were deductively coded using the AGT coding scheme.

Quantitative Differences Across Graphs

There were no significant differences across graph type. On average, each student predicted that he or she would perform 15–16% points better than their beginning score, with a standard deviation that ranged from 6% (self-focused upward) to 8.8% (comparative divergent downward trending). At least one student, however, predicted that he or she would do worse before he or she would do better for two graphs: self-focused downward-trending and comparative divergent downward-trending (see Table 3 for summary statistics of student predictions).

Overview of AGT Coded Segments

Students used language consistent with AGT 79 times. An overview of how students' language varied by graph type is presented in Figure 10, with each bar corresponding to a particular graph (e.g.,

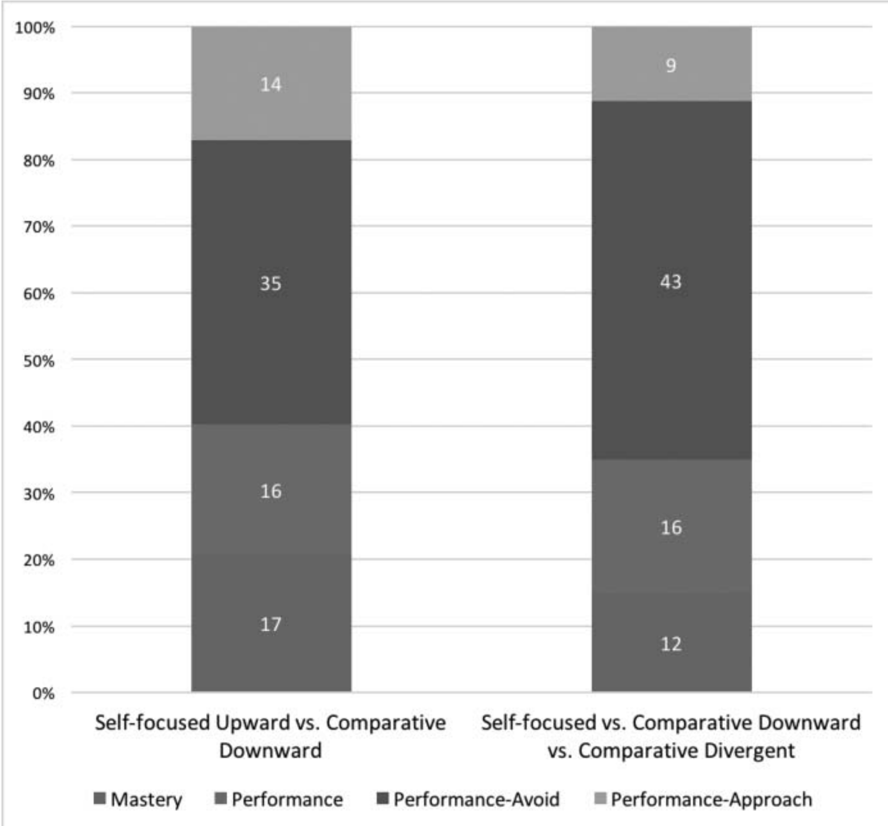

Figure 9. Overview of AGT coded segments as students chose most motivating graph.

the self-focused upward trending graph has 14 mastery related statements). Self-focused graphs yielded interpretations linked to mastery orientation; no other AGT sense-making language was used when students interpreted self-focused graphs. The results were more mixed for comparative graphs. While mastery language was still used throughout comparative graphs, the majority of language used paralleled the performance construct, which lacked positive (wanting to outperform others) or negative (not wanting to fall behind others) dimensions. Performance-avoid was seldom used (four times in the comparative upward trending graph, and once in the divergent graph).

Completing Graph Trend Lines, Examples of Student's Responses (RQ3)

Table 4 illustrates the range of responses given when students were asked to complete trend lines and explain their reasoning. Overall, there were multiple examples of students interpreting graphs through a mastery perspective—even when the graphs themselves had comparative information. Notably, there were no performance statements for graphs without comparative information,

Table 3. Summary statistics of differences across graph type

	Mean	*SD*	Minimum	Maximum
Self-focused upward trending	15.3	6.0	0	27
Comparative upward trending	15.3	6.6	0	27
Self-focused downward trending	16.5	8.7	−9	35
Comparative downward trending	16.1	7.8	0	35
Comparative divergent trending	12.3	8.8	−7	30

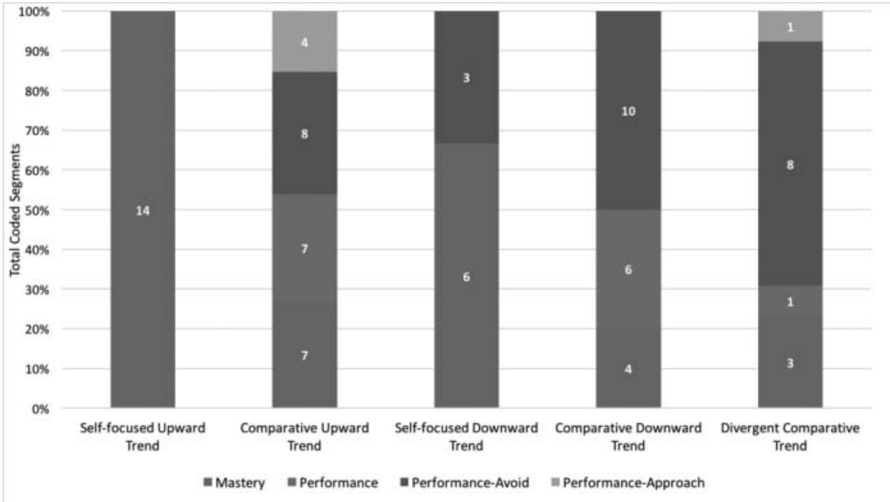

Figure 10. Overview of coded segments by graph type and AGT codes.

suggesting that graphs may shape how students calibrate their effort given a visualization. As AGT would posit, graphs with comparative information always yielded performance statements.

Limitations

There are a multitude of visualizations, and this study is limited to line graphs representing achievement over time in a manner that is either self-focused or comparative. This was a deliberate decision—the literature on graph comprehension suggests that line graphs in particular afford interpretations that make it easy to distinguish between two lines that communicate distinct information (in this case, individual performance and the class average). Unfortunately, relying on line graphs also limits the potential inferences made by this study. For example, this study cannot speak to whether or not other graph types (e.g., bar graphs) would yield similar results.

Aside from being limited by the types of visualizations used, there were also necessary limitations regarding what achievement data were depicted. Line graphs have the potential to depict various types of academic scenarios, and the ones chosen for this study were artificial; four of five of them also posed an unlikely academic scenario: students' progress displayed in a manner that almost exactly paralleled the class average. Real academic settings are messier. Students, moreover, were also never shown to be ahead of the class average. Such a graph would likely yield different interpretations.

Another limitation is the fact that this study was not conducted within an authentic learning analytics application environment, or an authentic learning environment. This study relies on hypothetical situations of achievement. While this makes the results compelling for different reasons, the fact remains that students looking at their actual achievement data may respond differently to representations of it.

Discussion

Learning analytics-based educational technologies have the potential to foster students' capabilities to pose nuanced questions such as "how does my performance this week compare to last week?," "what resources might I utilize to engage in this course differently?," or "how am I doing in relation to my peers?" Such questions may move learners beyond merely being able to accomplish a task, and toward more complex thinking about how the task will be—or has been—accomplished. In this way, learning analytics is well positioned to help students understand their own learning processes (Winne, 2017), and can also be used as a tool to meaningfully personalize learning experiences

Table 4. Coded student statements when predicting future performance

Graph name	Graph example	Mastery statements	Performance statements	Performance-avoid statements	Performance-approach statements
1a		If I'm progressively getting better as the time goes on, why would I go downhill? I can just keep going up from there. (Female 1)			
1b		Because it's like 70% or 75%, I would still want to do better whether or not the class was higher than me or not. So . . . (Female 4)	It's like win–win. I'm up there with everybody else but I'm also doing my best. (Female 5)	I decided going up 'cause I'll probably just try harder, 'cause me not doing as well other people motivates me to do better. (Female 7)	When I compare myself to other people I feel like I'm not . . . I don't know, I'm just so competitive that I always wanna beat other people even though, if my best is good then that's good. I don't know. It's a double win. (Female 5)
2a		I just knew that I have to study really hard to get back where I was or surpass where I was. I need to get it to working real quick. (Female 9)			
2b		Because, even though the class average is better than mine, I know that I'm not responsible for the rest of the class, I'm responsible for my own grades . . . (Female 10)	My average wasn't as high as the class's average. So I just went on how I thought the class would do over time, and then just based mine off of that. (Male 2)	I decided to draw it a little higher than the other one because I want to be at least at the class average and not anything lower. (Female 6)	
2c		It affects me more rather than just if the whole class was doing bad. So I know, okay, I need to get hold of myself. I am the one that's slacking. Not the teacher, not anyone else. (Male 5)	I feel like the class average is gonna motivate me to work harder. (Female 12)		Again, probably seeing everybody else do better. I wanna do better. (Female 13)

(Aguilar, 2017). Insights generated by learning analytics-based educational technologies also have the potential to motivate students in new and interesting ways, and lead them to make choices unknown to them before. Despite these possibilities, it is important to be mindful of the potential maladaptive motivational consequences introduced by such technologies.

The potential for learning analytics-driven technologies is predicated on how they communicate information to their users. Thus, all learning analytics-based educational technologies have the potential to interfere with learners' established processes and workflows for learning. This study adds to our understanding of such processes by exploring student interpretations of a necessary component of learning analytics-based educational technologies: the representations they use to communicate academic performance information. Specifically, the communicative affordances of line graphs were examined. Results indicated that graphs deliberately designed with self-focused versus comparative information were perceived in a manner consistent with AGT, for which the constructs captured the salient responses to graphs with comparative information. These results suggest the mastery/performance distinction within AGT maps onto representations that are self-focused and comparative. Students, moreover, found that comparative graphs designed with performance information affordances were "more motivating."

When asked to compare graphs with self-focused versus comparative information in order to determine which they find "more motivating," students' explained their answers in ways consistent with AGT, suggesting that the information environment that emerges through learning analytics applications—if designed with comparisons and with self-focused information—evokes thought processes more consistent with an AGT framework. The momentum behind the design and implementation learning analytics applications stems from the proposition that they will lead to adaptive outcomes for the learner, and that any added information affordances are necessary for the good of the learner. Even if we assume this is the case most of the time, it is still important to note that each representation utilized by a learning analytics application makes assumptions regarding how viewers ought to make sense of their own learning.

By design, each learning analytics-based dashboard, or early warning system, foregrounds information that is believed to be important, salient, and actionable, and backgrounds (or removes) unimportant information. These decisions are typically not under students' control, and while lack of student control is present in any educational setting to some degree (e.g., a teacher displaying some student information at the expense of other work), it is nonetheless important to study the effects of design decisions.

The narrowing of students' choices over what they see is justifiable if designs are examined for their assumptions and evaluated for their efficacy. Doing so "unpacks" what information is deemed important and what information is deemed unimportant; such decisions are not idle ones, but are instead the result of assumptions of those who build and deploy learning analytics-based educational technologies. The true affordances of any learning analytics application (i.e., what it is possible for the users to uncover about their own learning by using a learning analytics tool) are not built in a vacuum, but rather originate from the beliefs, values, understandings, constraints, opportunities, and pressures held or faced by those who construct a given learning analytics application. Any "perceived" affordance (Norman, 1999) embedded in a learning analytics application, then, is a product of the aforementioned contextual circumstances that give rise to the application, and the conventions, feedback loops, and constraints that come to define a learning analytics tool.

Design Implications

This study lends support to the notion that visualizations foreground information that can be simultaneously helpful and hazardous to students, depending on both the person and the academic context. Results suggest the following maxims that can guide the design of visualizations in academic settings: (1) Never assume that more information is better; (2) anticipate and mitigate against potential misinterpretations—or harmful alternative interpretations—of visualizations; and (3) always suggest a way for students to improve. Each is discussed in turn.

There is an understandable tendency within the learning analytics research community to find, acquire, analyze, and communicate (i.e., represent) any and all data that may be relevant in learning contexts. This tendency is well intentioned; however, findings from this study suggest that students may not need more information to learn more. Indeed, more information may be harmful. Results from this study suggest that the more information is embedded in a visualization, the more variability there will be in how it is interpreted. (Students had both mastery and performance interpretations once comparative information was added to a relatively simple line graph, for example.) Thus, more information is not always better. Instead, more information introduces more variability in interpretation. This is not necessarily a down side; designers of visualizations should, however, understand as many of the potential perceived affordances of their designs as possible before students are exposed to them.

This leads to the second maxim that can guide the design of visualizations: "anticipate and mitigate against potential misinterpretations—or harmful alternative interpretations—of visualizations," which refers to the idea that visualizations should not harm students' ability to learn. "Harm," is used broadly, and subjectively. Harm can be socioemotional, academic, context specific, and student specific. Student A, for example, may wish to see comparative information, but comparative information may lead this student to attribute failure to an uncontrollable source. This student may instead benefit more from self-focused academic performance visualizations. Student B, on the other hand, may not wish to see comparative information that may actually hold him or her accountable.

Regardless of the visualization used, maxim three ("always suggest a way for students to improve") serves as a check for those interested in developing learning analytics-based educational technologies. Comparative information, for example, may only be harmful to certain students, and only if those students see their failures relative to their peers as a dead end. If failure is detected, visualized, and communicated to students, then a way to mitigate, eliminate, or otherwise address said failure ought to also be made available. Herein lies the great potential of learning analytics applications. A struggling ECON 101 student may, for example, need to see the class average because the course imposes a curve, thus tying each student's performance to that of his or her peers. An ethical learning analytics application, then, should supply this information, but also should pair it with resources that students can bring to bear when they face challenges. Each student would, hypothetically, have his or her own personalized set of triggers for this information to be displayed. Conversely, the resources themselves could be personalized.

Conclusion

Learning analytics-based educational technologies are the instantiation of the goals of various stakeholders, including the institutions that implement them. Embedded in the design of a given learning analytics technology are various decisions regarding what sort of information may or may not help students, as well as the form that information takes. Rather than being distinct from decisions made in a one-on-one scenario (e.g., when a student meets an advisor), learning analytics automate this decision-making process and extend the decision-making powers of those who design them, as well as enabling stakeholders to scale their decisions to thousands of students.

This study explores how those in a specific student population (students at risk of academic challenges or failures) interpret visualizations of academic information. It suggests that at-risk students may have specific needs in this respect. Many sought comparative information despite being sensitive to comparing poorly to peers. Comparative work will have to be done, however, to determine whether there are any differences for at-risk students' interpretations of visualizations compared to those of other college students. This tension between what information at-risk students are drawn to versus what information may be most appropriate is an important one. If effectively designed, visualizations have the potential to give students information attuned to their needs, rather than information design to help the "average" student—one who exists only as a construct of research. The potential of learning analytics-based educational technologies is one of inhabiting a mediating role, one that is defined by helping students make decisions that they are already contemplating, through providing feedback and resources previously unavailable to them (or available slowly, via cumbersome channels). Consequently, learning analytics that utilize visualizations have the potential to be valuable sources of information. They are scalable and can work within large university data infrastructures, or even K–12 settings. Yet unless the manner in which students make sense of visualizations is better understood, providing them with more information may not always be better, and may in fact lead to maladaptive outcomes, such as suggesting that they ought to attend to other students' success more than their own (i.e., trading a mastery goal for a performance goal). This study is an initial step in better understanding the role of visualizations in the new information environment that is nearing ubiquity in higher education. It has shown that the manner in which academic information is represented should not be taken lightly. Not only do visualizations themselves afford certain types of understanding, but students interpret them in complex ways.

Received: 6/13/17
Revised: 11/1/17
Accepted: 11/2/17

Acknowledgments. The author thanks the University of Southern California's Provost's Postdoctoral Scholars Program for its support, as well as Dr. Stuart Karabenick, Dr. Barry Fishman, Dr. Steven Lonn, and Dr. Stephanie Teasley, who nurtured an early interest in learning analytics applications.

Author Notes

Dr. Stephen J. Aguilar is a Provost Postdoctoral Scholar at the USC Rossier School of Education. His areas of expertise include motivation and self-regulated learning as they relate to the design and implementation of educational technologies. He specializes in learning analytics. Please address correspondence regarding this article to Stephen J. Aguilar, Rossier School of Education, University of Southern California, 3470 Trousdale Parkway, 600B Waite Phillips Hall, Los Angeles, CA 90089–4036, USA. E-mail: aguilars@rossier.usc.edu

ORCID

Stephen J. Aguilar http://orcid.org/0000-0003-2606-067X

References

Aguilar, S. J. (2017). Learning analytics: At the nexus of big data, digital innovation, and social justice in education. *TechTrends*, *26*(1), 1–9. http://doi.org/10.1007/s11528-017-0226-9

Barron, K. E., & Harackiewicz, J. M. (2001). Achievement goals and optimal motivation: Testing multiple goal models. *Journal of Personality and Social Psychology*, *80*(5), 706–722. http://doi.org/10.1037//0022-3514.80.5.706

Berger, J.-L., & Karabenick, S. A. (2011). Motivation and student's use of learning strategies: Evidence of unidirectional effects in mathematics classrooms. *Learning and Instruction*, *21*(3), 416–428. http://doi.org/10.1016/j.learninstruc.2010.06.002

Bodily, R., & Verbert, K. (2017). Trends and issues in student-facing learning analytics reporting systems research (pp. 309–318). In X. Ochoa, I. Molenaar, & S. Dawson (Eds.), *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 309–318). New York, NY: ACM Press, New York, NY:. http://doi.org/10.1145/3027385.3027403

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, *18*(6), 683–695. http://doi.org/10.1080/13562517.2013.827653

Cousin, G. (2009). *Researching learning in higher education: An introduction to contemporary methods and approaches*. New York, NY: Routledge.

Diana, N., Eagle, M., Stamper, J., Grover, S., Bienkowski, M., & Basu, S. (2017). An instructor dashboard for real-time analytics in interactive programming assignments. In X. Ochoa, I. Molenaar, & S. Dawson (Eds.), *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 272–279). New York, NY: ACM Press. http://doi.org/10.1145/3027385.3027441

Duval, E. (2011). Attention please!: Learning analytics for visualization and recommendation. In G. Conole & D. Gašević (Eds.), *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 9–17). New York, NY: ACM Press. http://10.1145/2090116.2090118

Elbadrawy, A., Studham, R. S., & Karypis, G. (2015). Collaborative multi-regression models for predicting students' performance in course activities (pp. 103–107). In P. Blikstein, A. Merceron, & G. Siemens (Eds.), *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 103–107). New York, NY: ACM Press. http://doi.org/10.1145/2723576.2723590

Elliot, A. J. (2005). A conceptual history of the achievement goal construct. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 52–72). New York, NY: Guilford Press

Elliot, A. J., & McGregor, H. A. (2001). A 2 × 2 achievement goal framework. *Journal of Personality and Social Psychology*, *80*, 501–519.

Elliot, A. J., Murayama, K., & Pekrun, R. (2011). A 3 × 2 achievement goal model. *Journal of Educational Psychology*, *103* (3), 632–648. http://doi.org/10.1037/a0023952

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology*, *54*(1), 5–12. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/3346808

Harackiewicz, J. M., Barron, K. E., Carter, S. M., Lehto, A. T., & Elliot, A. J. (1997). Predictors and consequences of achievement goals in the college classroom: Maintaining interest and making the grade. *Journal of Personality and Social Psychology*, *73*(6), 1284. http://doi.org/10.1037/0022-3514.73.6.1284

Harackiewicz, J. M., Barron, K. E., Pintrich, P. R., Elliot, A. J., & Thrash, T. M. (2002). Revision of achievement goal theory: Necessary and illuminating. *Journal of Educational Psychology*, *94*(3), 638–645. http://doi.org/10.1037//0022-0663.94.3.638

Harrison, S., Villano, R., Lynch, G., & Chen, G. (2015). Likelihood analysis of student enrollment outcomes using learning environment variables. In P. Blikstein, A. Merceron, & G. Siemens (Eds.), *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 141–145), New York, NY: ACM Press. http://doi.org/10.1145/2723576.2723621

Hollands, J. G., & Spence, I. (1992). Judgments of change and proportion in graphical perception. *Human Factors the Journal of the Human Factors and Ergonomics Society*, *34*(3), 313–334.

Karabenick, S. A. (2004). Perceived achievement goal structure and college student help seeking. *Journal of Educational Psychology*, *96*(3), 569–581. http://doi.org/10.1037/0022-0663.96.3.569

Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). A learning management system-based early warning system for academic advising in undergraduate engineering. In J. A. Larusson & B. White (Eds.), *Learning analytics: From research to practice* (pp. 103–119). New York, NY: Springer. http://doi.org/10.1007/978-1-4614-3305-7_6

Lam, A. C., Ruzek, E. A., Schenke, K., Conley, A. M., & Karabenick, S. A. (2015). Student perceptions of classroom achievement goal structure: Is it appropriate to aggregate? *Journal of Educational Psychology*, *107*(4), 1102–1115. http://doi.org/10.1037/edu0000028

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2013). Issues, challenges, and lessons learned when scaling up a learning analytics intervention. In D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 235–239). New York, NY: ACM Press. http://10.1145/2460296.2460343

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2014). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior*, *47*, 1–8. http://doi.org/10.1016/j.chb.2014.07.013

Meece, J. L., Blumenfeld, P. C., & Hoyle, R. H. (1988). Students' goal orientations and cognitive engagement in classroom activities. *Journal of Educational Psychology*, *80*(4), 514–523. http://doi.org/10.1037//0022-0663.80.4.514

Meyer, J., Shamo, M. K., & Gopher, D. (1999). Information structure and the relative efficacy of tables and graphs. *Human Factors*, *41*(4), 570–587.

Midgley, C., Hruda, L. Z., Anderman, E. M., et al. (2000). *Manual for patterns of adaptive learning scales*. Ann Arbor, MI: University of Michigan.

Midgley, C., Kaplan, A., & Middleton, M. (2001). Performance-approach goals: Good for what, for whom, under what circumstances, and at what cost? *Journal of Educational Psychology*, *93*(1), 77–86. http://doi.org/10.1037//0022-0663.93.1.77

Miller, W. L., Baker, R. S., Labrum, M. J., Petsche, K., Liu, Y.-H., & Wagner, A. Z. (2015). Automated detection of proactive remediation by teachers in reasoning mind classrooms. In P. Blikstein, A. Merceron, & G. Siemens (Eds.), *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 290–294). New York, NY: ACM Press. http://doi.org/10.1145/2723576.2723607

Pintrich, P. R., & de Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33–40. http://doi.org/10.1037/0022-0663.82.1.33

Rheinberg, F., Vollmeyer, R., & Rollett, W. (1999). Motivation and action in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 1–27). Cambridge, MA: Academic Press

Santos, J. L., Govaerts, S., Verbert, K., & Duval, E. (2012). Goal-oriented visualizations of activity tracking: A case study with engineering students. In S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 143–152), New York, NY: ACM Press. http://doi.org/10.1145/2330601.2330605

Scheffel, M., Drachsler, H., Kreijns, K., de Kraker, J., & Specht, M. (2017). Widget, widget as you lead, I am performing well indeed! In X. Ochoa, I. Molenaar, & S. Dawson (Eds.), *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 289–298). New York, NY: ACM Press. http://doi.org/10.1145/3027385.3027428

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (1996). *Motivation in education*. New York, NY: Pearson.

Senko, C., & Miles, K. M. (2008). Pursuing their own learning agenda: How mastery-oriented students jeopardize their class performance. *Contemporary Educational Psychology*, *33*(4), 561–583. http://doi.org/10.1016/j.cedpsych.2007.12.001

Shah, P., & Carpenter, P. A. (1995). Conceptual limitations in comprehending line graphs. *Journal of Experimental Psychology: General*, *124*(1), 43.

Shah, P., & Freedman, E. G. (2009). Bar and line graph comprehension: An interaction of top-down and bottom-up processes. *Topics in Cognitive Science*, *3*(3), 560–578. http://doi.org/10.1111/j.1756-8765.2009.01066.x

Shim, S. S., Ryan, A. M., & Cassady, J. (2012). Changes in self-esteem across the first year in college: The role of achievement goals. *Educational Psychology*, *32*(2), 149–167. http://doi.org/10.1080/01443410.2011.627837

Steele, C. M. (1997). A threat in the air. *American Psychologist*, *52*(6), 613–629.

Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology*, *69*(5), 797–811.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research*, *45*(1), 89–125.

Tinto, V. (1987). *Leaving college*. Chicago, IL: University of Chicago Press.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500–1509. http://doi.org/10.1177/0002764213479363

West, D. M. (2012). *Big data for education: Data mining, data analytics, and Web dashboards*. Brookings Institution. Retrieved from https://www.brookings.edu/wp-content/uploads/2016/06/04-education-technology-west.pdf

Winne, P. H. (2017). Leveraging big data to help each learner and accelerate learning science. *Teachers College Record*, *119*(3), 1–24.