Perceived Motivational Affordances: Capturing and Measuring Students' Sense-Making Around Visualizations of their Academic Achievement Information

by

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Dedication

Para mi mama y papa,
Guillermina Aguilar y Luis Manuel Aguilar;
porque yo no sería quien soy hoy sin
sus sacrificios, apoyo, y amor.

To my wife,
Perica Cheyvette Bell;
for always challenging me when I needed it—
you inspire me to be better.

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Table of Contents

List of Tables

List of Figures

List of Appendices

Abstract

Learning analytics aggregates and analyzes educational data in order to improve learning outcomes. The efficacy of learning analytics is predicated on the validity of techniques used to uncover patterns about student learning and engagement, *and* the ways in which these patterns are communicated (i.e., represented) to various stakeholders. How students understand representations of their learning, and whether or not those representations motivate them in positive ways, is not well understood. This dissertation addresses this gap in the literature and examines student motivation in relation to learning analytics through two complementary studies framed by Achievement Goal Theory—a prominent theory of students' academic motivation.

Study 1 utilizes qualitative interviews (n = 60) to investigate how students at-risk of college failure interpret visual representations (i.e., visualizations) of their potential academic achievement. Findings suggest an interplay between the information communicated by visualizations and students' own inclinations towards the information they wished to see. Visualizations designed with self-focused affordances (i.e., showing only the participants academic information), for example, evoked statements focused on personal growth from students when they interpreted the graphs (i.e., mastery statements). Visualizations with comparative information (i.e., that cast an individual student's performance against the class average), however, evoked responses that ranged from helping students hold themselves accountable to disheartening students so much that they would rather give up than try harder.

Study 2 designed and validated the Motivated Information-Seeking Questionnaire (MISQ) using a college student sample drawn from across the country (n = 551). The MISQ measures constructs that are parallel to—but distinct from—mastery, performance-avoid, and performance approach goal orientations as theorized by Achievement Goal Theory.

Confirmatory Factor Analysis (CFA) was used to internally validate the MISQ scales, resulting in validation of the performance-approach information-seeking (PAIS) and performance-avoid information-seeking (PVIS) dimensions. Results of external validation indicated that PVIS and PAIS were empirically distinguishable from performance-approach and performance-avoid achievement goal orientations. Multiple regression analysis supported the predictive power of PVIS and PAIS with regard to students' emotional responses to certain types of visualizations and to what they attributed their success and/or failure, after controlling for relevant demographic characteristics.

Each of the studies contributes to our understanding of the motivational implications of visualizations in academic settings. Taken together, these studies increase our knowledge of the various dimensions students use while interpreting visualizations, and uncovered tensions between what students want to see, *versus* what it might be more motivationally appropriate for them to see. Importantly, the MISQ can be used to better understand the role of students' information seeking tendencies with regard to their interpretation of various kinds of visualizations. Both studies suggest three maxims for the design and use of visualizations: 1) *Never assume that more information is better; 2) Anticipate and mitigate against potential harm;* and 3) *Always suggest a way for students to grow.* Each is important for advisors, who serve as mediators between students and visualizations of academic information; learning analytics researchers and designers, who are responsible for the design of visualizations of academic achievement information; and institutions, who use learning analytics applications as *de facto* student-facing representatives of themselves.

Chapter 1: Introduction

The emerging field of learning analytics that is dedicated to using various sources of data to uncover patterns in student learning has grown in popularity within the higher education community. Two years ago the 2014 Horizon Report, published jointly by the New Media Consortium and the EDUCAUSE Learning Initiative, predicted that learning analytics—which provides "ways...to improve student engagement and provide a high-quality, personalized experience for learners"—was within one year of being adopted widely (L. Johnson, Adams Becker, Estrada, & Freeman, 2014 p. 38). Learning analytics has the potential to transform the ways that institutions of higher education address issues of retention, learning, and student success by enabling them to use large amounts of "data about learners in order to improve learning" (Clow, 2013). Users of learning analytics include students (Arnold & Pistilli, 2012; Wise, 2014) and intermediaries, such as academic advisers (Krumm, Waddington, Teasley, & Lonn, 2014; Lonn, Aguilar, & Teasley, 2014). Research foci within the learning analytics community include studying students' behaviors in online learning systems (Brooks, Demmans Epp, Logan, & Greer, 2011), predicting student outcomes (Fancsali, 2011; Teplovs, Fujita, & Vatrapu, 2011), and discussing the various methodological approaches associated with learning analytics (Atkisson & Wiley, 2011b; Suthers & Rosen, 2011).

As an applied field, learning analytics research often informs the design of various applications intended to communicate the patterns in student learning that quantitative analyses uncover (see Arnold & Pistilli, 2012; Duval, 2011; Krumm et al., 2014; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Wise, Zhao, & Hausknecht, 2013, for examples). What distinguishes these learning analytics applications from traditional modes of academic feedback (e.g., grades, or comments on an essay) is their capacity to extract data from user interactions with the learning environment, transform it through algorithms and computational processes, and "load" it onto applications designed to provide feedback that is personal, information rich, and quickly disseminated (Lonn, Aguilar, & Teasley, 2013). These applications, in theory, help stakeholders (e.g., students, administrators, academic advisors) identify trends both within and across different students, courses, and/or student populations by providing "actionable" information intended to support evidence-based decision making (Arnold & Pistilli, 2012).

To date, the field has focused heavily on the development of quantitative techniques and the application of those techniques to detect patterns in educational settings (Elbadrawy, Studham, & Karypis, 2015; see Harrison, Villano, Lynch, & Chen, 2015; Kennedy:2015dz Miller et al., 2015, for examples). Less attention, however, has been paid to how the resulting analytics are represented to various stakeholders, and the effects of those representations. While there has been some interest in the study of representations in the form of data visualizations (Duval, 2011; Santos, Govaerts, Verbert, & Duval, 2012; Verbert et al., 2013), only limited work has focused on better understanding how visualizations affects learning and non-cognitive factors associated with learning (e.g., motivation).

The efficacy of learning analytics is predicated on the validity of techniques used to uncover patterns about student learning and engagement, *and* the ways in which these patterns are communicated (i.e., represented) to various stakeholders. Consequently, errors, bias, misunderstandings, and/or misinterpretation within either analytics or their representations can result in communicating actionable information that is potentially misleading, or that contains unintended messages. Thus, if the goal of learning analytics applications is to communicate actionable information, and learning analytics applications utilize visualizations to represent actionable information, then how various stakeholders make sense of those visualizations warrants study.

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, 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 stereotype threat (Steele, 1997; Steele & Aronson, 1995).

While there have been calls to include non-cognitive factors into analytic frameworks (e.g., Gray, McGuinness, Owende, & Carthy, 2014), little work has explored students' sense-making around visualizations, or measured their potential information seeking goals in relation to visualizations. Recent work suggests that more work is required, especially with regard to the potential influence of visualizations on student motivation. Lonn, Aguilar, and Teasley (2014), for example showed that visualizations found within implementations of learning analytics applications potentially influence the academic motivation of students at-risks students' for dropping out of college. This suggests that students may not always be agnostic towards the information learning analytics applications provide. 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 suggesting that they ought to attend to other students' success more than their own (i.e., trading a mastery goal for a performance goal).

Problem Statement

This dissertation addresses a gap in the literature with respect to student motivation in relation to learning analytics by investigating how students make sense of visualizations of their own academic information. Since visualizations are a core component of how information is represented within learning analytics applications, they can potentially influence a number of motivational processes. These include: how students engage with their learning environments based on their perceived level of competence (Elliott, Elliott, & Dweck, 1988); students' orientations towards the value of achieving their goals (Battle & Wigfield, 2003; Wigfield & Cambria, 2010; Wigfield & Eccles, 2000); the perceived utility of accomplishing a task (Hulleman, Godes, Hendricks, & Harackiewicz, 2010); the associated costs and identity formation involved with achieving their goals (Perez, Cromley, & Kaplan, 2014); students' self-efficacy (Bandura, 1977; 1997); and students' goal orientations toward the learning task (Elliot & McGregor, 2001; Elliot, Murayama, & Pekrun, 2011; Elliott et al., 1988; Rawsthorne & Elliot, 1999).

While there are many different sense-making processes and outcomes that are worthy of study in relation to visualizations of academic information, I focus on motivation because it is the process of initiating and sustaining behaviors for the purposes of accomplishing a goal, which is a necessary component of academic success. If one isn't motivated enough to attempt a task or pursue a goal, then it is unlikely that said task or goal will be accomplished. *Academic* success, then, is predicated on students' motivation to succeed in educational contexts.

There are various well-established approaches for studying student motivation. Chief among these is Achievement Goal Theory (Elliot, 2005; Elliot & McGregor, 2001), Expectancy-Value Theory (Wigfield & Cambria, 2010; Wigfield & Eccles, 2000), Attribution theory (Weiner, 1979; 2005; 2010), and Albert Bandura's Social Cognitive Theory (Bandura, 1977; 1997). This dissertation draws from each theory at various points, but is principally oriented around Achievement-Goal Theory (AGT) which focuses on why students are motivated to accomplish their academic work, positing that they can be oriented toward performance (i.e., defining their success based on where they stand in comparison to others) or mastery (i.e., defining their success relative to their own growth) (Elliot & McGregor, 2001). I propose that performance and mastery can be made more or less relevant in visualizations based on whether or not they show information that is comparative (performance) or individualized (mastery).

Specifically, I examine how students attend to the display of information related to their academic performance, and incorporates aspects of the graph comprehension literature (Meyer, Shamo, & Gopher, 1999; e.g., Pinker, 1990; Shah & Mayer, 1999), when relevant. I focus on at-risk students because they represent a group that is likely to receive institutional support, and are thus more likely to be sent messages about their learning by an institution, or agents within that institution (Tinto, 1987; 1993; 1996). As they are more susceptible to these messages, there is a sense of urgency to better understand how at-risk students make sense of visualizations.

Organization of Dissertation

This dissertation is divided into five chapters. Chapter 2 serves as a review of the relevant literature. I begin with learning analytics, paying particular attention to visualizations used within student-facing learning analytics applications. I then provide overview of the science behind graph comprehension, which informs the visualizations designed for both studies. I then move to the theories of students' academic motivation: Self-Efficacy, Achievement-Goal Theory, and Expectancy-Value Theory, paying particular attention to the latter two theories since they serve as the most relevant theoretical frames for the two studies. The chapter concludes by reviewing literature focused on understanding "at-risk" student populations—which is a student population of particular interest given their need for additional institutional support, technologically mediated or otherwise.

Chapter 3 focuses on the qualitative investigation of student sense-making around visualizations of their academic performance (study one). Chapter 4 focuses on the assessment of a survey instrument designed to measure students' information seeking goals (study two). I conclude with Chapter 5, where I discuss the implications of both studies to the theories of student motivation they are framed by; explore the implications for educational practitioners and learning analytics designers; discuss the limitations of both studies; and outline future work.

Overview of Studies, Research Objectives, and Research Questions

There are two primary research objectives: 1) to better understand at-risk college students' attitudes towards visualizations of their academic performance, and 2) to develop and validate an instrument designed to measure the constructs that drive college students' information-seeking goals.

Framing of Studies

Both studies are framed by Achievement-Goal Theory (AGT), but also utilize the insights of other prominent motivational theories (e.g., Expectancy-Value Theory, Attribution Theory). In both studies, I hypothesize that students also orient themselves towards their academic information via similar goals which are parallel to—but distinct from— performance and mastery as described in the AGT literature. Both studies serve the dual purpose of capturing how students interpret visualizations of their academic information, and measuring those attitudes.

Study 1: Qualitative Investigation of Students' Sense-making of Graphs

Study 1 (Chapter 3) is a qualitative investigation that utilizes semi-structured interviews of current and former University of Michigan Summer Bridge students to capture how they made sense of academic information when it was presented to them visually. An *a priori* scheme was used to deductively code and analyze transcripts, and was utilized to address RQ1 – RQ3 below. The remaining research questions (RQ4 – RQ7) were addressed inductively. Answers to RQ4-RQ7 are intended inform the future designs of various data visualizations, or speak to general attitudes of self-efficacy. This study aims to capture students' sense-making of visualizations, and helped define some of the pilot items tested in the second study.

Research questions for Study 1. The following research questions are posed:

RQ1) When asked to think about their performance at the midpoint in a hypothetical course, how do at-risk college students make sense of the following representations?

Representations that depict individual performance as trending in the following ways:

- upward
- upward and compared to the class average (which is parallel to and above their own average)
- downward
- downward and compared to the class average (which is parallel to and above their own average)
- in a manner that is divergent from the class average in a negative direction.

RQ2) When comparing graphs with similar trends to one another, but different Achievement Goal Theory affordances/design elements, which graphs do students choose as "more motivating," and how do they explain their reasons for their decision? Are student's explanations consistent with language AGT might predict, e.g., "I like it because it shows me getting better and better?"

RQ3) How do students predict their future performance using graphs showing upward trends, downward trends, and divergent trends?

- How do students express their motivation as they explain how they decided to draw compete a line representing their progress in the course?
- Is there an observable difference between the lines completed for graphs with mastery design elements versus performance design elements?

RQ4) What are the salient academic events, incidents, or previous experiences that students recall when remembering representations of achievements?

RQ5) What information do students say is helpful/unhelpful in the graphs they are shown?

RQ6) What additional information do students state would be helpful for them to see?

RQ7) What graph to students' state is most representative of the type of student they are, and does their explanation of their selection align with what sort of student they said they were at the beginning of the interview?

Study 2: Quantitative Investigation Measuring Students' Information Seeking Orientations

Study 2 (Chapter 4) is an investigation that utilizes cognitive interviews and confirmatory factor analysis (CFA) to validate a survey instrument designed to measure the underlying constructs that may be responsible for certain orientations towards visualizations of academic information. In addition to 22 pilot items, participants were also presented with one of three graphs of potential academic progress, and answered questions designed to capture what they attributed their success (or failure), and their emotional reaction to the graphs. Half of the participants were also Pell Grant recipients, indicating low-income status.

Research questions for Study 2. The following research questions are posed:

RQ1) Does revising the AGT instrument: Patterns of Adaptive Learning (Midgley et al., 2000), with language that focuses on information representation yield stable and reliable factors?

RQ2) Is there empirical support for scales that measure general motivational orientations towards information representation in a manner that is parallel to, but distinct from, the PALS scale?

The following research questions investigate the possible relationship between the proposed constructs, students' affective responses to various representations, and students' attributions once they are shown a graph that depicts them failing or succeeding in a given course. The following research questions are exploratory, without a priori assumptions or hypotheses for how the proposed constructs will relate to students' attributions toward their academic performance in a course.

RQ3) Assuming a stable and reliable factor structure is found, are any of the proposed constructs predictive of:

a. Students' stated emotional reactions to specific graphical representations (e.g., doing worse than the class average).

b. Students' attributions (e.g., stable, internal, and controllable) for their performance after seeing specific graphical representations.

c. Students' selections of specific areas of representations that are salient, or otherwise important features (e.g., selecting the end of a downward trending line in a lime graph).

d. Academic outcomes of interest (e.g., GPA).

Significance of Research

Findings contribute to the fields of educational psychology by utilizing prominent theories of student motivation and applying them to an understudied context: the information environment of students as instantiated by typical learning analytics visualizations. This is a pressing concern; with the ubiquity and ease of access to students' academic information, visualizations become necessary components of learning analytics applications in order to communicate meaning.

This dissertation also contributes to the emerging learning analytics field: providing information relevant to the design of learning analytics applications for use by students. The instrument validated in Study 2 can be integrated to the design process, and thus inform the design of visualizations. Learning analytics researchers and designers could, for example, have students take a survey to measure their general motivational orientation towards visualizations, and ensure that students' personalized dashboards only presented visualizations that were shown to be associated with adaptive outcomes for students *like them*. Conversely, such an instrument could also 'protect' students from representations that are predicted to be associated with maladaptive outcomes.

Chapter 2: Literature Review

Visualizations are a core component of how actionable information is represented within learning analytics applications (Pardo, 2014; Siemens, 2013). When students are the primary users of an application that utilizes visualizations, academic information they may not have attended to otherwise (such as the class average for an exam) can be foregrounded, implying its importance. It is unclear what effect this information has on students; they may, for example, change how they approach a particular assignment (e.g., an exam). They may also alter their academic motivation for an entire course by focusing on the success (or failure) of others instead of their own learning (i.e., replacing a mastery orientation with a performance orientation). Students at-risk of academic failure are especially attuned to messages about their performance, and may place more emphasis on messages communicated to them via learning analytics applications developed by their institution. How visualizations are interpreted by (at-risk) students—and the relationship between their interpretations and their academic motivation—is not well understood, and is a focus of this dissertation.

The analytic framework utilized to study the phenomenon of sense-making in relation to visualizations draws on various fields. This chapter organizes key understandings of those fields, and thus draws on learning analytics literature to organize various types of visualizations; leverages the graph comprehension literature to contextualize the potential affordances of specific visualizations; and discusses how various theories of students' academic motivation can be used as theoretical frameworks to understand the sense-making processes that are evoked when students interpret particular visualizations. Attention is also paid to literature focused on at-risk college student to better understand their potential susceptibility to messages communicated through visualizations.

Organization of Literature Review

The first section provides context for organizing (potential) visualizations within learning analytics applications. It focuses on a select number of visualizations within learning analytics applications that are either explicitly designed for student use, or can potential be used by students. The second section discusses graphs—and their particular affordances—as instantiations of visualized information.

The third section outlines how the preeminent theories of academic motivation serve as a useful framework to investigate students' "motivational sense-making" of visualizations depicting academic performance. Specifically, it covers Bandura's theory of Self-Efficacy, Achievement Goal Theory, Expectancy-Value Theory, and Attribution Theory. The section concludes with a discussion of the intersection between theories of student motivation and learning analytics applications.

The fourth section of this literature review discusses how Vincent Tinto's model of college persistence and retention can be utilized to position learning analytics applications as agents of the institutions that design them; understood in this way learning analytics applications can play a particularly important role in the academic success (or failure) of at-risk students. This chapter concludes by connecting the reviews the goals for Study 1 and Study 2, paying particular attention to the gaps in the literature each study is meant to address.

Learning Analytics Applications

Early learning analytics research has focused on understanding student behaviors in online learning systems (Brooks et al., 2011), predictive modeling of student outcomes (Fancsali, 2011; Teplovs et al., 2011), and learning analytics methodologies (Atkisson & Wiley, 2011a; Suthers & Rosen, 2011). To date, learning analytics research has developed various tools that utilize predictive models and/or machine learning algorithms to help students, educators, and administrators make informed choices regarding study habits (Leeman-Munk, Wiebe, & Lester, 2014; Wise, 2014), teaching practices (Gasevic, Mirriahi, Long, & Dawson, 2014), and institutional policy (Arnold et al., 2014).

Given the affordances of various types of data found in educational contexts (e.g., intuitional records, learning management system log files, student surveys, students' academic records), learning analytics research often culminates in the design and implementation of an application that aggregates, processes, and applies a set of analytic techniques to data in order to provide stakeholders with new insights into their respective educational contexts (Lonn et al., 2013). When the design of applications is the goal, learning analytics researchers typically design tools that represent student data in a way that is "actionable" (Arnold & Pistilli, 2012). Actionable information is designed to suggest a solution to an academic challenge, provide students with resources they were unaware of (Arnold & Pistilli, 2012; Campbell, DeBlois, & Oblinger, 2007), or showcase evidence that might reinforce prior helpful behaviors. In general, actionable information encourages choices that improve the likelihood of achieving a pre-determined set of desirable outcomes, such as earning a desired grade in a class, finding the optimal sequence of courses to take for a given major (Nam, Lonn, Brown, Davis, & Koch, 2014), or improving student retention rates.

While various applications are designed for users other than students (Aguilar, Lonn, & Teasley, 2014; Arnold et al., 2014; Lonn et al., 2014), many are also designed with the explicit intention of being used by students. These 'student-facing' applications come with their own set of affordances, and utilize various forms of representations and/or data visualizations to communicate actionable information to students.

Little is known about how students interpret visualizations of academic performance displayed within student-facing applications, though it is clear that many visualizations are designed to communicate actionable information. This review of the learning analytics literature provides examples of various visualizations. It is organized into two sections: 1) applications which use visualizations that afford ego-centric (inward looking) interpretations, and 2) applications which use visualizations that afford comparative (outward looking) interpretations.

Applications Utilizing Visualizations that Afford Ego-Centric Interpretations

The following section describes applications that focus on visualizing students' individual academic performance information. Applications which provide potentially comparative information (i.e., any information about other students, the class average, etc.) are described in a subsequent section.

Capella's "Competency Map". The competency map, developed by Capella University, is designed to give feedback to students in a manner that encourages them to participate in the courses they are enrolled in (Grann & Bushway, 2014). Rather than communicate grade information, it is designed around communicating a set of "competencies" that are determined by the course. Figure 1 below shows one student view of how competencies are measured: percentage of objectives completed serve as the primary focus of the displays.

Figure 1. Examples of competency map visualizations from (Grann & Bushway, 2014)

Initial analysis of the competency map found that students who used it were more likely to persist in their program, and were also more likely to demonstrate mastery over the course's competencies, after controlling for perceived course engagement (Grann & Bushway, 2014). There has been no published research focused on how students interpret individual visualizations.

Purdue's "Course Signals". One of the original applications developed as a learning analytics application, Course Signals was designed by Purdue University as a dashboard application meant to identify at-risk students at the course level and provide "real time" feedback to them before they found themselves past the point of no return, i.e., failing their courses (Arnold & Pistilli, 2012). To do this, Course Signals uses students' demographic data, grade data, and data taken from the learning management system (LMS) as a proxy for course engagement to build a predictive model that "signals" how a student is doing via traffic light indicators (where red is preforming poorly, yellow is in danger of preforming poorly, and green is preforming well).

Faculty members have access to information showing how all of their students are doing (Figure 2), while students see their progress after receiving an email from their faculty member. Analysis of Corse Signals suggests that the majority of students (74%) found their traffic signal motivating in a positive sense, and were more likely to seek help when they needed it (Arnold & Pistilli, 2012). More recent analysis, however, questions the accuracy of the 74% figure (Caulfield, 2013). Regardless, there does not seem to be published research that explores how students actually *interpret* their “signals” from a motivational perspective, despite evidence suggesting that they find said signals motivating.

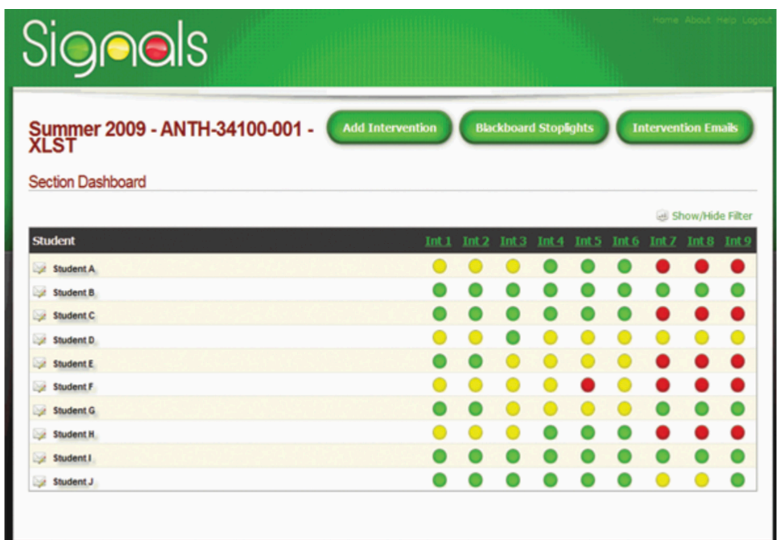


Figure 2. Course Signals Dashboard (Arnold & Pistilli, 2012)

Applications Utilizing Visualizations with Comparative Affordances

The following section describes applications that visualize students’ individual academic performance information *and* include information about their peers, either in aggregate or individually.

iSpot. iSpot is an "informal networked learning environment" designed to facilitate sharing of observations "about nature" (K. Thompson et al., 2013). Users can post their observations online, and share them with a like-minded community. iSpot encourages users to post their observations and engage with the online community, and has tools that allow users to develop expertise via a "reputation" system that is accessible to every registered user. As a platform, iSpot is designed to build and communicate levels of expertise for each user as it relates to classifying various plant and animal organisms within its system (K. Thompson et al., 2013). As users participate and gain expertise, they are awarded icons that demonstrate their levels of expertise (Figure 3).

Users of iSpot are encouraged to participate through extrinsic incentives tied to their online reputation within the system. Specifically, the authors state that "[t]he knowledge status of a member is rewarded through his or her activities within the network, and the degree of activities will affect his or her reputation, represented and communicated to learners through the display of icons" (K. Thompson et al., 2013). This is operationalized by giving each user an icon which visualizes their level of expertise. Icons are visible to the entire community.

Figure 3. iSpot Reputation System, with badges next to user names (Clow & Makriyannis, 2011)

Thompson et al. (2013) have discussed using the data generated by iSpot to uncover the relationship between icons and use of the system, as well using social network analysis to better understand the community that uses it. This work is ongoing, but does not utilize any particular theoretical framework, focusing instead on usage patterns within the system (e.g., do icons encourage users to log into the system).

The University of Michigan's "Student Explorer." Student Explorer is primarily used by academic advisers (Krumm et al., 2014). The online system aggregates students' online grade book data, and presents that data to advisors though a graphical user interface. (See Lonn et al., 2013, for details on how it was implemented in a large university setting). For each course presented within Student Explorer, students are designated with an ''E3'' status of ''Encourage'' (green), ''Explore'' (yellow), or ''Engage'' (red), a categorization derived from overall percentage of points earned, distance from the course average, and Learning Management System (LMS) course website logins (Figure 4).

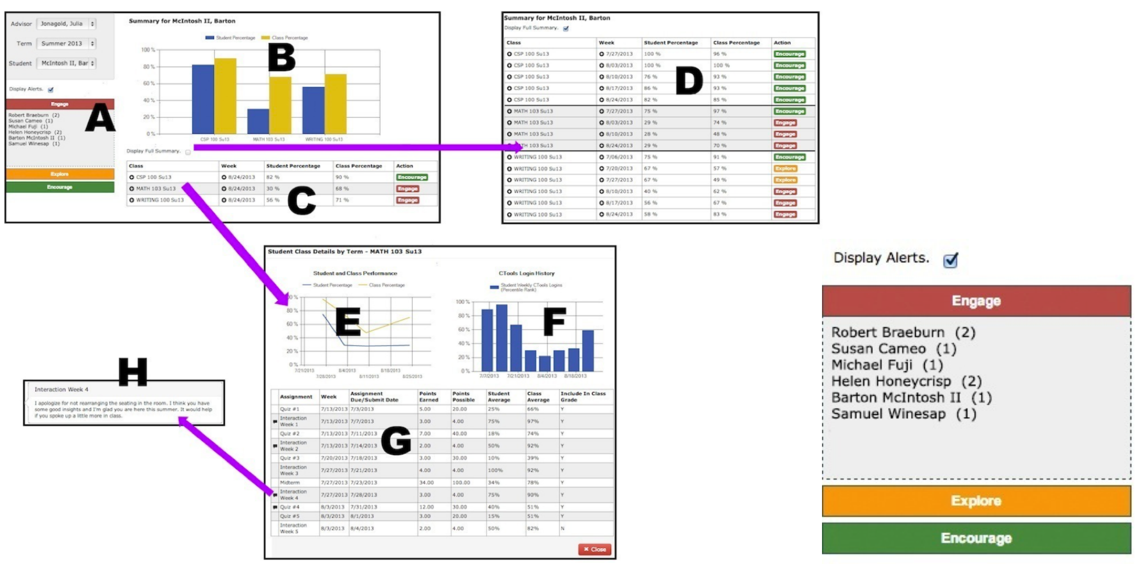


Figure 4. Student Explorer Dashboard (Lonn et al., 2014)

Despite not being a student-facing system, recent research has demonstrated a relationship with students' exposure to the tool itself and their academic motivation, suggesting the possibility that exposure to visualizations of academic performance may actually lead to an acceleration in students' already decreasing mastery orientation, as conceptualized by AGT

(Lonn et al., 2014). The study by Lonn, Aguilar, and Teasley (2014) is the first to frame the study of a learning analytics application with motivation theory.

UMBC's "Check My Activity." The University of Maryland, Baltimore County's "Check My Activity" (CMA) tool was designed with comparison explicitly in mind (Fritz, 2011). CMA allows students to compare their own usage of the university's LMS to that of their (anonymized) peers. It also enables students to compare their grades in a course to an anonymized "Grade Distribution Report," which contained aggregate grade information. Analysis is ongoing, however preliminary qualitative data yielded the following responses when students were asked whether or not they would use the CMA:

> "Yes, because I would feel more pressure to be with the rest of the crowd and be just as participating as them so I don't look bad.
>
> "[Y]es because we can actually compare how well we are doing in the class, or how we can work harder like 'other students—who click into the site' to improve our studying skills,"(Fritz, 2011 pg. 96).

While these data seem to have motivational content (e.g., "pressure to be with the rest of the crowd), the motivational implications of the CMA tool have not been studied.

Graph Comprehension

Far from a modern phenomenon introduced by the advent learning analytics applications, depictions of information have been found across different cultures (Galesic & Garcia-Retamero, 2011) and time periods (Zacks & Tversky, 1997). Graphs are powerful types of visualizations because they do not (simply) represent the data that underlies them in straightforward manner, but instead they enable the viewer to derive global meaning (i.e., about "more" than the graph), and/or local meaning (i.e., about specific features within the graph itself) (Simcox, 1984). Information that is visualized graphically can be interpreted in any order, e.g., beginning with a key or legend first (Karkin, 1987). It is unsurprising, then, that many learning analytics applications use graphs to visualize actionable information (e.g., Lonn et al., 2014; Verbert et al., 2013). This section introduces the communicative affordances of line graphs and bar graphs, further situating the phenomenon motivational sense-making in relation to graphs used within learning analytics applications.

Graph types

Meyer et al. (1999) showed that graphs are more effective means of presenting information when compared to tables, so long as the information they present is non-random and well-structured. The literature on graph comprehension suggests that different types of graphs (e.g., bar graphs, lines graphs, and 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, i.e., main effects.

The affordances of different graphs are not simply a product of graphs themselves. In a series of experiments, Zacks & Tversky (1997) showed that when subjects were given verbal descriptions of data, they were more likely to draw bar graphs when the descriptions emphasize comparisons, and are more likely to draw line graphs when the verbal descriptions emphasize trends. They also showed that the reverse was true. Their work suggests that bars and line graphs tend to may have stable communicative affordances (Zacks & Tversky, 1997).

Line graphs. Line graphs are usually designed to depict linear relationships between two or more variables (Shah & Carpenter, 1995). They are well suited to communicating information that is "discrete"—each line represents a unique piece of information, and do so in a way that implies trends (i.e., the slope of the line). Line graphs also facilitate quicker judgements of change when compared to bar graphs (Hollands & Spence, 1992).

Line graphs can be designed in a manner that depicts complicated relationships. Departures from linear relationships (e.g., line graphs that begin to resemble curvilinear relationships), and reversal of trends (e.g., an upward trend abruptly changing to a downward trend) both affect how a graph may be interpreted (Shah & Carpenter, 1995). "Trend reversals" in line graphs (i.e., upward trending patterns abruptly changing to downward trending patters, or the reverse) also cause misinterpretation. Graphs that are more linear and symmetrical tend to lend themselves to interpretations of "global" patterns (Carswell, Emery, & Lonon, 1993).

Bar graphs. Bar graphs facilitate the comparison of two or more values, and are best equipped to communicate information that is "discrete," because the bars themselves are separate from one another (Zacks & Tversky, 1997). They also differ from line graphs in that differences between bars need not be exaggerated in order to effectively communicate differences (Simcox, 1984). There is also a tendency for individuals to misinterpret bar graphs when there is a conflict between the information communicated via spatial features *versus* information conveyed through textual means, e.g., a bar graphs with higher bars representing *lesser* quantities (Okan, Garcia-Retamero, Galesic, & Cokely, 2012). This suggests that the informational affordances of bar graphs work best when depicting positive values.

Graphs and Learning Analytics Applications

Of the tools described above, line graphs were most often used to visualize academic performance over time. This is in accord with the affordances of such graphs; line graphs are best equipped to depict trend information, and because each line is interpreted as a discrete quantity, it is possible to use more than one line to represent various pieces of information (e.g., a line representing a student's average in a class and a line for the class average, as is the case in Student Explorer).

Motivational Frameworks for Studying Visualizations

The manner in which students interpret graphs contained within learning analytics applications has not been studied from a motivational perspective. This section builds the necessary framework for such an investigation. The study of students’ academic motivation is vast, interdisciplinary, and encompasses various theoretical perspectives. Chief among these is Achievement Goal Theory (Elliot, 2005; Elliot & McGregor, 2001), Expectancy-Value Theory (Wigfield & Cambria, 2010; Wigfield & Eccles, 2000), Attribution theory (Weiner, 1979; 2005; 2010), and Albert Bandura’s Social Cognitive Theory (Bandura, 1977; 1997). Each theory, moreover, provides specific insights into how students may interpret graphs depicting their academic performance.

Achievement Goal Theory

Achievement Goal Theory (AGT, Barron & Harackiewicz, 2001; Elliot et al., 2011; Elliot & McGregor, 2001) is a framework for understanding the motivational constructs that relate to adaptive and maladaptive ways students can engage with their learning environment. AGT states that students engage with learning environments differently based on their orientation towards the value of achievement and their perceived level of competence. Contemporary AGT has been structured to include four related goal orientations that all describe students' motivation for accomplishing academic tasks and approaching the work associated with them. These constructs are “mastery-approach,” “mastery-avoidance,” “performance-approach,” and “performance-avoidance” (Elliot & McGregor, 2001). This dissertation explores AGT as it relates to the *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 constructs provide useful theoretical frames to investigate how students interpret visualizations.

Mastery approach/avoid. 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). In general, “mastery goals focus on (and celebrate) the development of competence and task mastery, whereas performance goals focus on the demonstration of competence relative to others’’ (Rawsthorne & Elliot, 1999 pg. 326). 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). In short, they ‘learn for learning’s sake.’

Students with mastery-avoid orientation focus their attention inward; they make “intrapersonal” assessments that may involve reflecting on how well they understand the material being taught to them (Elliot & McGregor, 2001). Mastery-avoidance has been shown to be positively related to students’ avoidant help-seeking behavior (Karabenick, 2003). While theoretically interesting, there is limited applied work on the construct of mastery-avoid.

Performance approach/avoid. 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 et al., 1988).

Contextual factors. 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-avoidance 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 applications provide an additional digital environment that students are exposed to. This dissertation hypothesizes that similar AGT-inspired constructs are at work when one compares the information environment afforded by learning analytics applications, and brick-and-mortar contexts, such as the classroom. Mastery and performance constructs are likely to emerge, albeit with different characteristics which are intertwined with information seeking orientations, rather than learning goal orientations.

Expectancy-Value Theory

Expectancy-Value Theory (EVT, Eccles & Wigfield, 2002; Wigfield, 1994; Wigfield & Cambria, 2010; Wigfield & Eccles, 2000) seeks to explain student motivation by first examining students' "expectancies" toward a given task, and then the values associated with succeeding (or failing) at said task. For students, these expectancies serve as *de facto* self-evaluations of the likelihood of success or failure when a task is attempted. These expectancies and values are presumably informed by information students have at hand. Given that learning analytics applications are designed to provide *actionable* information through visualizations, it is likely that students' interpretations of visualizations influence both expectancies and values.

Expectancies. Students can have a range of expectancies for both general domains (e.g., math), and specific tasks (e.g., a math exam). Importantly, expectancies also have a temporal dimension, and can be proximal (i.e., a task requiring immediate—or near immediate—attention), or distal (i.e., a task that will be done sometime in the future). Students' expectancies for success have been shown to be predictive of self-regulated learning behaviors (VanZile-Tamsen, 2001), such as resource management (Pintrich, 1999). "Resources" may refer to asking more knowledgeable students for help, taking advantage of on-campus study centers, asking the instructor questions during office hours, etc. (see Makara & Karabenick, 2013 for more information). Depending on the data that drives a visualization, the actionable information afforded by a given application has the potential to influence both general (e.g., a STEM major) and task specific (e.g., an exam in a STEM course) expectancies.

Task-values. Regardless of when a task occurs, EVT posits that any particular task attempted by a student also has an associated "task-value." There are four different components to task-values, described below.

Attainment. "Attainment" value is defined as the "personal importance [placed upon] doing well on a task" (Eccles & Wigfield, 2002). Within the EVT framework, personal importance is also intertwined with a learner's identity as it relates to the task. Since a student's identity is necessarily a product of a larger socio-cultural context, various identity norms may also be inherited and influential as the attainment value of a particular task is calculated by a student. Eccles et al. refer to this as the "cultural milieu" that student find themselves embedded in. This milieu helps explain certain phenomena that hinder academic performance, such as stereotype threat (Steele, 1997), which has been shown to adversely affect the performance of African American students (Steele & Aronson, 1995) and female students (Spencer & Quinn, 1999) during math assessments.

The design of visualizations within learning analytics applications presume certain attainment values, either implicitly or explicitly. It is this presumption that makes information "actionable." If there were little reason to do well on a task, then it would not be a part of a visualization because visualizations are intended to foreground what's important (Pardo, 2014). Consequently, visualizations within learning analytics applications may afford "attainment" interpretations.

Intrinsic value. Intrinsic value focuses on internal processes. Specifically, a given task might evoke feelings of joy or flow as it is being done (Csikszentmihalyi, 1993). Since intrinsic value is largely focused on internal perceptions of a task, the construct has also been shown to be predictive of high mastery goals in students (e.g., Liem, Lau, & Nie, 2008). This is supported by theory, since mastery goals are also generally characterized as being intrinsic (Elliot, 2005).

Research has shown that some female students attach higher intrinsic value to obtaining higher education due to a "personal wellness" orientation, which is a move away from a more cautious orientation driven by avoiding the negative consequences associated with the pursuit of an advanced degree (like limiting family planning decisions (Battle & Wigfield, 2003). Such students, then, attach intrinsic value to goals that are still somewhat distant. Understood in this way, intrinsic value is both complex in origin and dynamic in practice, conditioned on various possibilities and inclinations a student may possess, or wish to possess. While visualizations are unlikely to *change* the intrinsic value of any given task (since that value comes from the student), they can still *support* students' intrinsic values (if what they value is visualized), or they can suggest that what they value is unimportant.

Utility value. Utility value depends on current goals or distant goals. Whether or not these goals can be characterized as intrinsic or extrinsic, however, is a matter of interpretation; students' goals may be internalized and intertwined with their aspirational identities (intrinsic), or they may be anchored on the wishes of their parents (extrinsic).

In addition to shaping how students might approach an academic task, utility value has also predicted farther reaching decisions, such as the types of courses students choose to enroll in (Bong, 2001). It is unsurprising, then, that utility value is the focus of intervention designs, such as "relevance" interventions. Such interventions explicitly ask students to connect a given task to their own lives through a writing exercise in order to increase perceived utility value; these interventions have proved successful in both laboratory and classroom settings (Hulleman et al., 2010).

Learning analytics applications—and the actionable information communicated by visualizations of academic performance—can be best understood as also communicating utility value to students, in subtitle or explicit ways. Students enrolled in a course that imposes a curve, for example, may interpret visualized comparative information through the lens of utility, using it to calibrate their own efforts. Whereas students who are not enrolled in a course with a curve would likely not have the same interpretations.

Cost. Cost refers to an internal calculation associated with opportunity costs associated with a given task, e.g., doing well on an exam or choosing to major in a STEM field. Students wishing to do well on an exam, for example, may need to delay their own gratification (Bembenutty & Karabenick, 1998) and be attentive during instruction; whereas students pursuing a STEM career would have to factor in other long-term costs. Costs are ubiquitous and can factor into any calculation for success at some level because accomplishing tasks requires students to make decisions based in a finite set of choices, each with its associated expectancy-value calculation. Perez et al. (2014), for example, found in their longitudinal study of identity development in STEM retention, that perceptions of cost when majoring in STEM fields were negatively related to identity development with an exploration component (e.g., reflection). They also found, moreover, that identity exploration was positively related to how competent students felt in STEM, and how much they valued it. The opposite was found to be true for identity development without exploration.

Visualizations within learning analytics applications may foreground (or hide) certain costs associated with success or failure. If a given visualization is ego-centric and avoids depicting comparative information, for example, then it is unlikely that poorly performing students would be feel the “cost” of being below average. Conversely, if a student was exposed to a line graph visualization which showed their class average sharply diverging from the class average line, they might grow upset. The actionable information communicated by visualizations, then, may frame cost in powerful ways.

Social Cognitive Theory (Self-Efficacy)

Albert Bandura’s (1977, 1997) argues that self-efficacy is shaped by an individual’s ability to perform, and plays a role in goal-setting behaviors and positive academic outcomes

(Zimmerman, Bandura, & Martinez-Pons, 1992). Specifically, "personal efficacy are derived from four principal sources of information: performance accomplishments, vicarious experience, verbal persuasion, and physiological states, " (Bandura, 1977) pg. 191). High self-efficacy in students has been linked to cognitive engagement and performance (Pintrich & de Groot, 1990b).

Academic self-efficacy (i.e., self-efficacy as it relates to student's beliefs about their abilities to perform in academic settings, (Schunk, 1991) has been shown to have direct and positive relationships to mastery goals, task-values, and performance-approach goals (azar, Lavasani, Malahmadi, & Amani, 2010), and has also been shown to be positively associated with course grade outcomes (Bong, 2001). Self-efficacy has also been shown to be positively associated with college's students first year performance, and can act as a mediator to students' ability to cope with academically demanding situations (Chemers, Hu, & Garcia, 2001). As a construct, academic self-efficacy has been demonstrated to accounts for variance in college grade outcomes above and beyond traditional standardized academic measures (e.g., ACT scores) when measured at the end of students first semester (Gore, 2006).

Over time, if students are exposed to numerous visualizations of their academic performance, then the additional information afforded by the sum of those visualizations likely influences students' academic self-efficacy—or at least serves as additional information that is used to calibrate and form a sense of academic-self efficacy. (If a student is constantly shown to be below average, for example, then they will likely develop low academic self-efficacy.) Bandura's theory, then, serves as a useful orientation towards the long-term study of the effects of visualizations.

Attribution Theory of Motivation

Attribution Theory (AT, Weiner, 1979; 1985; 2005; 2010) posits three types of attributions that define how individuals interpret casualty in a given achievement scenario, i.e., it is a 2 x 2 x 2 theoretical model. According to AT, attributions can be classified by their locus (internal or external), stability (stable or unstable), and controllability (controllable or uncontrollable). Figure 5 provides a visualization of the possible classification combinations for attributions.

Causes of Success and Failure, Classified According to Locus, Stability, and Controllability

	Internal		External	
Controllability	Stable	Unstable	Stable	Unstable
Uncontrollable	Ability	Mood	Task difficulty	Luck
Controllable	Typical effort	Immediate effort	Teacher bias	Unusual help from others

Figure 5. Weiner's 2 x 2 x 2 Model of Attributions (Weiner, 1979)

A student, for example, might attribute their failure on an exam to an external cause (e.g., having their exam graded by a harsh grader), which is uncontrollable (they can't control the actions of a grader), and stable (the grader has a reputation of being a harsh). Each dimension is described below in more detail. The various dimensions of a given attribution can influence students' academic motivation (Weiner, 1979). Each dimension is described in more detail below.

Locus (internal/external). Locus refers to how one interprets the locus of origin that contributed to a success or failure. A given consequence, for example, can be attributed to either internal causes (e.g., I chose to do this; I am responsible for this) or an external cause (e.g., This resulted because of the actions of another; I had no choice in the matter) (Weiner, 1979).

Research with minority college students has shown that their attributions for success can vary and evolve over time, with some students attributing initial difficulty to poor preparation, while others attributed poor performance to lack of studying (Griffin, 2006). Visualizations within learning analytics applications likely play a role in helping students determine a locus of control regarding their own academic performance. For example, in a given course it is possible that everyone does poorly on an exam. If a visualization depicts only individualized (ego-centric) information, then it is implied that individual students were responsible for their poor performance. If, however, a class average is added, and it is shown that many people also did poorly, then the locus of control is less straight forward, and may shift to an instructor who wrote an unreasonably difficult exam.

Stability (stable/unstable). The second dimension posited by Weiner argues that, regardless of internal/external dimensionality, causes can also be stable, or unstable. I can, for example, attribute my success in school to my inborn ability as a student (stable), or I can attribute it to the fact that I tend to study a lot before exams (unstable, as I can always choose to not study) (Weiner, 1979).

A study of college honors students found a positive relationship between self-rating of talent (a internal, stable, and uncontrollable trait) to how much talent contributes to success; gender differences were also found, with males being shown to be less likely to report effort as important when it came to their own personal talents (Siegle, Rubenstein, Pollard, & Romey, 2010). Visualizations that build over time (e.g., a line graph constructed over a term), may play a role in developing students' beliefs about whether or not their performance is stable, or unstable. A line with a slope of zero, for example, would imply stability—whether or not that stability was attributed to the possession (or lack) of talent would depend on where it crossed the y-axis.

Controllability (controllable/uncontrollable). Controllability refers to whether or not causes are under the control of the person making the attribution. A four-year old's small stature, for example, is the cause for their inability to ride the 'big kid rides.' Under attribution theory this would be a cause that is "internal yet uncontrollable," (Weiner, 1985 pg. 551).Perry et al. (2001) found that college students who had reported having high academic control were more likely to be motivated and be effortful in their studies, when compared to students who reported having less academic control. Attribution retraining has also been used as an intervention to promote control beliefs in college students (Haynes, Perry, Stupnisky, & Daniels, 2009), with some success.

Attributions in the face of visualizations of academic performance. Regardless of what a particular visualization of academic performance depicts, it is possible that students will overlay a narrative that attributes a cause for the depicted outcome. For example, if a student sees a visualization depicting only their academic information, then their attribution for their performance may differ from an attribution made after seeing a visualization that depicts their information and a class average). Consequently, attribution theory serves as a useful theoretical perspective for understanding differences students may have in this respect.

Academically At-Risk College Students

College students who are academically "at-risk" have an above-average likelihood of experiencing various negative educational outcomes, including dropping out of college (Tinto, 1975; 1987); struggling in post-secondary educational settings (McLoughlin, 2014); having low academic self-concept due to perceived (or actual) academic deficiencies (Mealey, 1990); and being more susceptible to various forms of stereotype threat (Steele, 1997; Steele & Aronson, 1995).

At-risk students attending highly-selective institutions, moreover, are uniquely susceptible to developing a lower academic self-concept due to the competitive nature of the institutions they attend (Dai, 2004; Marsh & Hau, 2003). Recent studies have also shown that this effect is particularly sensitive to students who are exposed to information showing within-class comparisons, i.e., comparing their progress to that of their peers (Marsh, Kuyper, Morin, Parker, & Seaton, 2014). “At-Risk” is thus a designation that is predicated on contextual factors; the underlying causes and subsequent meaning of “at-risk” vary according to students’ demographic characteristics, and can be moderated, mediated, eliminated, or exacerbated by the characteristics of the institution at-risk students are enrolled in. Often learning analytics applications are designed with at-risk students in mind (e.g., Krumm, 2012). Vincent Tinto’s model of college retention is a useful way of framing learning analytics applications as non-human agents of the university that can influence students in powerful ways.

Vincent Tinto’s Model

Vincent Tinto’s model has remained an influential way to understand at-risk college student retention since its original introduction in the late 1970s (1975; 1987). It is a longitudinal model that explores persistence and dropout behaviors of college students, and was developed, in part, as a reaction against the then dominant idea that students dropped out of college due to personal deficiencies (see Tinto, 2006 for a discussion of the evolution of student retention literature).

His model outlines various systems that can encourage or discourage students to drop out of college, including: contextual features of students’ particular circumstances, such as the relationship between them and their respective institutions; students’ individual demographic characteristics (e.g., high school attended, socioeconomic status); and students’ expectations and motivations toward their ongoing success (Tinto, 1987; 1993; 1996). Tinto argues that students' relationship to their institution is not direct. Instead, students interact with members of that institution, e.g., faculty, administrators, and peers. The "institution" is thus not a fixed entity, but a fluid one that can change depending on its implicit and explicit representatives; this dissertation argues that learning analytics applications hold a similar positon, albeit an impersonal.

Since students will have necessarily personal and individual college experiences, college retention, according to Tinto, is a function of students' *integration* into the college system. How well a student is integrated into their institution is more predictive of their persisting through the college experience when compared to their entering characteristics and initial levels of commitment (Tinto, 1975). A student's success, then, rests how well the institution supports their integration into the larger academic and social community, and how well those efforts resonate with students themselves.

Tinto argues that integration is itself a multidimensional outcome. Students can, for example, integrate *academically,* or they can integrate *socially*. How—and how *well*—they ingratiate shapes their college experience. Students who befriend peers via close-knit student groups might integrate well socially, but if they perform poorly in their courses they may still drop out due to integrating poorly academically. Thus, how well students integrate into distinct institutional systems shape students' goals, and their commitment to the institution (see Figure 6 for Tinto's full theoretical model).

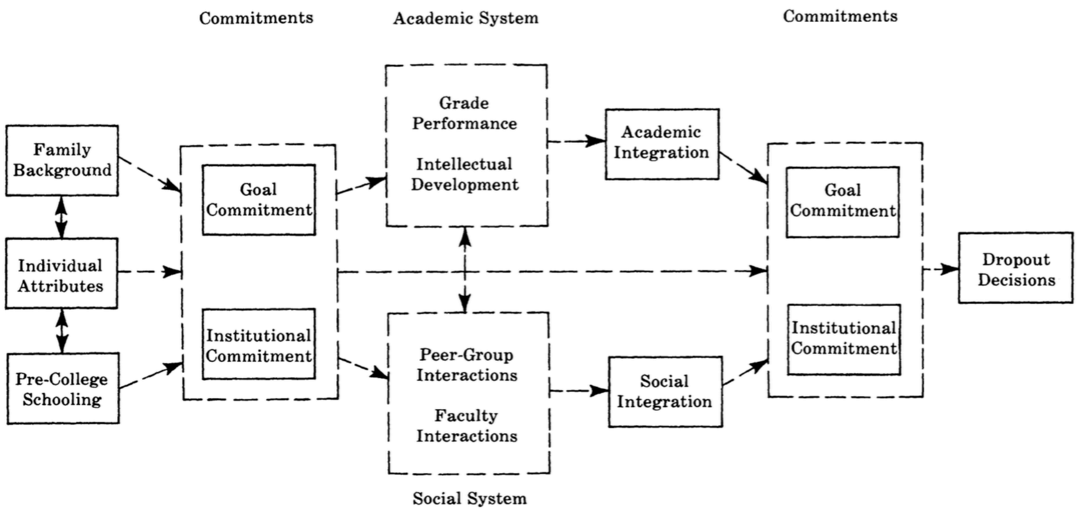


Figure 6. Tinto's "Conceptual Schema for Dropout from College" (Tinto, 1975)

While Tinto's model has never been used as a framework for the design of a learning analytics application, one can see how readily it could be applied to such an endeavor. Each box, for example, could correspond to actionable information intended to 'nudge' students towards a positive outcome. Understood in this way, the visualizations investigated in this dissertation would be nested within Tinto's "Academic System."

Contributions of Study 1 and Study 2

Each of the literatures reviewed above provide practical or theoretical insights into how this dissertation studies the processes and consequences of (at-risk) students interpreting visualizations of their academic performance deployed within learning analytics applications. This section expands on these insights, and situates them in relation to Study 1 and Study 2.

Implicit Argument of Learning Analytics

Learning analytics applications are the culmination of the embedded understandings, biases, and methods a learning analytics researcher or designer uses. The potential value for learning analytics applications are related to their capability to help students generate a set of imperatives for approaching various academic tasks, i.e., the extent to which the learning analytics applications provide “actionable” information to students (Arnold & Pistilli, 2012). The information and scope of feedback that grounds potential student-generated imperatives is distinct from traditional modes of academic feedback, and must be represented in some form. Representations are necessary components of applications that use, analyze, and report student data in hopes of increasing positive student outcomes (e.g., retention rates, course engagement, course performance), and/or decreasing negative student outcomes (e.g., drop-out rates, boredom).

The implicit argument within learning analytics is that the users of a given application will be able to take concrete steps toward better educational outcomes (broadly understood) because of the “actionable information” afforded by said learning analytics application. This presupposes that the affordances communicated by a given application—which operates under certain communicative modalities—are universally understood by the users. If this argument holds, then the “actionable information” communicated by an application (perhaps through visualizations of academic information) will be interpreted in the same way by each person who is exposed to it. Such an argument can be verified or challenged empirically, and serves as an open question explored by Study 1 and Study 2 of this dissertation. Specifically, I examine particular representations (Study 1 and Study 2), how students interpret them (Study 1 and Study 2), and also validate an instrument intended to capture general attitudes regarding students’ attitudes towards representations of their academic information (Study 2).

The above review has introduced an important distinction that is used throughout this dissertation: visualizations which depict a students’ individual academic performance information in an ego-centric manner (i.e., ignoring information of their peers), and visualizations which depict comparative academic performance information (foregrounding peer information). Each type of visualization has distinct affordances, the motivational implications of which is yet to be understood. Both Study 1 and Study 2 of my dissertation use this distinction to study how students make "motivational sense" of both ego-centric and comparative line graphs (Study 1 and Study 2), or the idea of having their academic information visualized (Study 2). I explicitly explore the notion that, if information communicated by a graph is actionable, then it may be actionable through certain well understood motivational mechanisms. These motivational mechanisms, moreover, may lead to positive or negative consequences.

Motivation and Visualizations of Academic Performance

AGT is well suited as a theoretical framework to explore the motivational antecedents of students' sense-making of visualizations (Study 1 and Study 2), while EVT and Bandura's theory of academic self-efficacy are well equipped to explore motivational consequences of visualizations (Study 1). Attribution theory contributes by providing a way to examine students' reasoning with regard to the causes for certain academic outcomes, as shown to them via graphs of academic performance (Study 2). Each study, moreover, contributes to the larger discussion of student motivation as it operates within the information environment that is necessarily created when showing students visualizations of their academic information.

Within the EVT framework, actionable information can be understood to be predicated on a set of possible courses of action that are, in turn, generated by questions students may ask themselves as they attempt a given task. Learning analytics applications are well positioned to provide students with a platform to engage with their information in a manner that is personal, dynamic, and capable of answering their particular questions that can influence both expectancies and task value. This processes is mediated through visualizations, which may consist of relevant information about students (Aguilar, Holman, & Fishman, 2013), or about their learning context (e.g., historical trends in a class, their own learning trends, etc.). An obvious point of where learning analytics and EVT intersect is the notion of cost, i.e., the socio-emotional costs associated with students being exposed to representations of their achievement via visualizations. Study one explores this head-on by analyzing students' reactions to graphs depicting potential academic information.

Learning analytics applications also have the potential to mediate each Bandura's self-efficacy mechanisms because they use visualizations to communicate performance accomplishments; their potential ubiquity can lead to various vicarious experiences for students; and representations of academic information are often paired with persuasive messages intended to encourage certain behaviors (Arnold & Pistilli, 2012).

Using AGT. While there is some work on preferences of visualizations within learning analytics applications (e.g., Vatrapu, Reimann, Bull, & Johnson, 2013), there does not seem to be literature that directly captures how visualizations of academic performance can induce, influence, or otherwise interact with students' academic motivation orientations. AGT does not take up the issue directly, however it suggests a framework for understanding and measuring the phenomenon of student sense-making around visualizations of academic performance. Study 1 and Study develop and utilize this framework, and posit that visualizations can lend themselves to being interpreted in ways that are conceptually similar to the constructs of mastery, performance-approach, and performance-avoid orientations outlined by AGT. Study 1 uses this uses this framework as an *a priori* coding scheme to code transcript segments, while Study 2 develops information seeking orientation constructs that parallel AGT constructs.

Using EVT. While AGT is posited to be conceptually relevant to understanding the antecedents of sense-making around visualizations of academic performance (i.e., the constructs that drive sense-making), EVT is used to investigate the potential motivational consequences that can be attributed to specific visualizations. Study 1 focuses on this question in detail, using EVT to inform the coding scheme used to sort student responses to particular visualizations.

At-risk College Students, Learning Analytics, and the New Information Environment

Were all students equal, there would be no need to discuss the subcategory of "at-risk" students. Unfortunately, for both systemic and contextual reasons there exist students who are at-risk of dropping out of college, as well as a multitude of other negative academic and personal outcomes that I have discussed elsewhere. Neither Tinto nor the literature on interventions designed to help at-risk college students, however, make explicit claims about *how* academic information is communicated to at-risk students. Yet, it is clear that information regarding students' academic standing and/or demographic background is required to differentiate them from students who are not deemed to be academically at-risk.

Due to their status, at-risk students are also exposed to various types of applications that are designed to lessen the likelihood of them experiencing poor academic outcomes. Learning analytics applications such as Course Signals (Arnold & Pistilli, 2012), represent one type of intervention. This dissertation explicitly makes the case that learning analytics applications serve as additional points of contact that can shape both the academic and social integration of students. For example, if a student is shown information that compares them to their peers when they log into a learning management system, this may in fact shape how integrated they feel in the class that generated the data, or the school as a whole; students who find themselves on the other side of unfavorable comparisons may begin to see themselves as not true members of the academic—or social—community.

Vincent Tinto's model proves to be particularly useful in understanding how this can influence at-risk students. In it, he defines institutions not as fixed brick-and mortar entities, but rather a collection of individuals that students can come into contact with at various points of their academic careers. These points of contact can occur in both formal academic settings, or informal social settings (Tinto, 1997). I extend Tinto's argument to also encompass learning analytics applications—and the representation of academic information contained within them—because applications are logical extensions of the goals set by stakeholders interested in helping at-risk students succeed. These stakeholders can include counselors, advisors, faculty, administrators, etc.

This gap in the literature is an important to address; as the section on learning analytics will show, students' information (i.e., data), is being collected, analyzed, represented, and disseminated in new ways—the (motivational) consequences of which have yet to be understood. This dissertation approaches this gap in the literature two distinct ways. First, Study 1 focuses explicitly on an at-risk population of college students; namely, summer bridge students identified as being at-risk of dropping out of college. In it I explore how they make sense of a particular form of academic information: graphs depicting academic performance. Study 2, on the other hand, explores at-risk students in a broader manner; survey data collected from students across the country indicate that 50% of self-identified Pell grant recipients, indicting their status as low-income students. This mixed sample is used to validate a survey instrument designed to measure students' information seeking orientations.

Chapter 3: Capturing Student Sense-Making of Academic Information Visualizations

Representations serve as proxies that communicate learning in powerful ways, and must be interpreted by students. In today's data-rich environment the landscape of representations in educational contexts is changing. The growth of learning analytics has led to the use of other representations of learning. Within learning analytics applications, these take the form of visualizations of educational data. Unlike letter grades, there is no clear precedent for interpreting the new wave of representations used within learning analytics applications.

Learning analytics is predicated on the ability to analyze learning data wherever it is found and communicate the resulting insights through a set of representations (Clow, 2013). These representations, in turn, can take the form of visualizations of academic performance that are embedded within learning analytics applications (e.g., Duval, 2011). Often, the developers of learning analytics applications are post-secondary institutions which design them to help students who are, or have the potential to be, at-risk of academic failure (Aguilar et al., 2014; Arnold & Pistilli, 2012; Fritz, 2011; Macfadyen & Dawson, 2010). When this is the case, the learning analytics application *itself* can be understood as a representative of the institution, which interacts directly with each student by communicating information intended to support them academically.

Consequently, learning analytics applications have the potential to shape students' experiences with specific instructors, courses, peers, the institution, or their own learning (Tinto, 1987; 1993; 1996). Visualizations play a major role in this process, and while there has been some work on understanding how—and for what purpose—visualizations within learning analytics applications are designed (e.g., Pardo, 2014; K. Thompson et al., 2013; Vatrapu et al., 2013; Verbert et al., 2013) there has been little (if any) work done investigating how students, especially those academically at-risk, make-sense of the visualizations they are presented with.

This study is a first step in that direction, and focuses primarily on motivational sense-making. It is framed by Achievement Goal Theory (Elliot, 2005; AGT, Elliot & McGregor, 2001) and Expectancy-Value Theory (EVT, Eccles & Wigfield, 2002; Wigfield & Cambria, 2010; Wigfield & Eccles, 2000), and explores the motivational implications of line graph visualizations. It examines how students make-sense of representations of academic performance which are designed with AGT affordances, i.e., information that foregrounds self-focused (mastery), or comparative (performance) information. It further contextualizes students' sense-making by organizing their interpretations of visualizations into categories informed by EVT (i.e., expectancies for success, utility values, and cost).

Research Questions

Specifically, this study poses the following research questions framed within AGT and EVT:

RQ1) When asked to think about their performance at the midpoint in a hypothetical course, how do at-risk college students make sense of the following representations?

Representations that depict individual performance as trending in the following ways[1]:

[1] See methods section below or Appendix A for images of the graphs

- upward
- upward and compared to the class average (which is parallel to and above their own average)
- downward
- downward and compared to the class average (which is parallel to and above their own average)
- in a manner that is divergent from the class average in a negative direction.

RQ2) When comparing graphs with similar trends to one another, but different Achievement Goal Theory affordances/design elements, which graphs do students choose as "more motivating," and how do they explain their reasons for their decision? Are student's explanations consistent with language AGT might predict, e.g., "I like it because it shows me getting better and better?"

RQ3) How do students predict their future performance using graphs showing upward trends, downward trends, and divergent trends?

- How do students express their motivation as they explain how they decided to draw the line?
- Is there an observable difference between the lines completed for graphs with mastery design elements versus performance design elements?

Answers to the following questions are intended inform the future designs of various data visualizations, or speak to general attitudes of self-efficacy.

RQ4) What are the salient academic events, incidents, or previous experiences that students recall when remembering representations of achievements?

RQ5) What information do students say is helpful/unhelpful in the graphs they are shown?

RQ6) What additional information do students state would be helpful for them to see?

RQ7) What graph to students' state is most representative of the type of student they are, and does their explanation of their selection align with what sort of student they said they were at the beginning of the interview?

Method

This study used semi-structured interviews to capture the ways at-risk college students interpret graphs designed to communicate academic performance. Semi-structured 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 (described below) to focus on sense-making as it relates to student motivation, and also enabled the development of an *a priori* coding scheme, while simultaneously leaving the flexibility to apply general inductive coding methods to opened-ended sections of the of interviews. The semi-structured 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; 5) Graph information evaluation. The materials, procedure, coding scheme, and participants are described below.

Participants

Students who participated in this study were drawn from the Summer Bridge program at the University of Michigan, and were recruited in partnership with the Comprehensive Studies Program (CSP), which administers the Summer Bridge program every summer. Summer Bridge cohorts are typically 200-250 students. A variety of criteria are used to identify students who participate in Summer Bridge (Fontenot, 2014), 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 CSP staff.

Context. The Summer Bridge program at the University of Michigan began in 1975 and is a part of the Comprehensive Studies Program (CSP). It assists non-traditional students' transition from high school to college by providing highly structured introductory coursework. Today, Bridge offers academic preparation, academic advising, and a community-building living environment to each cohort of incoming students, which generally numbers around 200. Students are expected to attend all of the Bridge classes and workshops, and also meet with their academic advisor on a weekly basis to discuss their progress or any challenges they may be experiencing (University of Michigan, n.d.).

Bridge students are enrolled in three seven-week courses: (1) a math course (remedial intermediate algebra, college-level intermediate algebra, or mathematical reasoning); (2) an English or Writing course; and (3) a freshman seminar that serves as an introduction to social science. Students are sorted into the mathematics and English/Writing courses based on a combination of placement exam scores, prior academic history, and intended major (Fontenot, 2014).

Recruitment. Email addresses from the 2013 (n = 217), 2014 (n = 201), and 2015 (n = 233) Summer Bridge cohorts were provided by program administrators. 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 email 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 CSP and the learning technologies that future students will use at the University of Michigan." Students were chosen to participate in the study on a first-come, first-served basis, and according to mutually overlapping schedules. Post-hoc analyses (below) were then conducted to determine if there were any systematic differences between wave one and wave two in comparison to the cohorts they were drawn from.

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 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).

Semi-structured Interviews. Interviews were conducted in two waves. Wave one 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 two 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 10-40 minutes, were recorded, and transcribed ($M_{minutes}$ = 25, *SD* = 5.2).

Final sample. The final sample for the study consisted of 18 males and 42 females. While this might imply that females were overrepresented, it is in fact representative since Summer Bridge typically serves twice as many females as it does males. Students interviewed, however, do not represent the larger 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
2 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 as the particular form of visualization for two reasons. First, they visualize linear relationships between two or more variables over time (Shah & Carpenter, 1995), and are well suited to study students' sense-making of graphs that show self-focused information (Graphs 1a and 2a), or comparative information (Graphs 1b, 2b, and 2c) over the course of an academic term. These design features also map onto Achievement Goal Theory (Elliot & McGregor, 2001), which posits similar dimensions: mastery (individual), and performance (comparative).

Second, 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 printed on paper. Each graph visualized 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. The first—Graph 1a—consisted of one line which 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 7).

Both upward trending graphs visualized a trend which 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 students' performance line, was always be 5% points higher (i.e., if the individual line showed 73% by week 14, then the class average lien showed 78%).

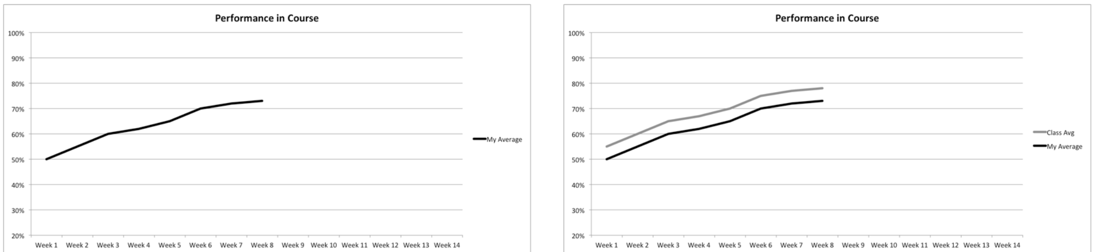


Figure 7. Graph 1a, self-focused (left) and Graph 1b, comparative (right)

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 which rose for the first five weeks, then steadily declined to a low of 65% by week eight. As with the upward trending graphs, the first graph (2a) depicted a student's individual performance, while the second graph (2b) depicted their performance as well as the average performance of the class (Figure 8). 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 six of the term.

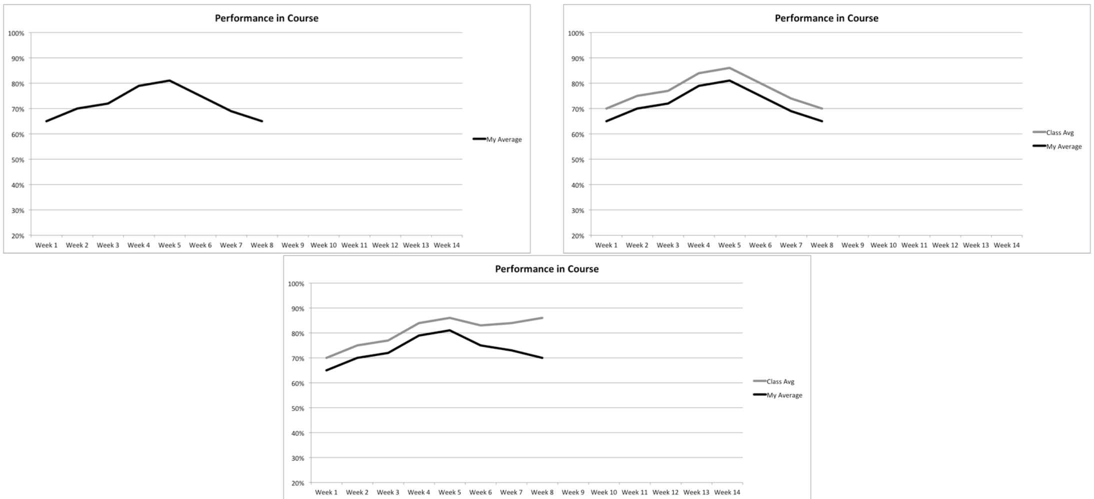


Figure 8. Graph 2a, individual (left), Graph 2b, comparative (right), and Graph 2c, divergent (bottom)

Procedure

Students recruited during wave one were interviewed during the winter term of the academic school year (January to May). Interviews were recorded, transcribed, and reviewed. Students recruited during wave two were interviewed during the summer term (June to August) with an adjusted interview protocol (described below). At the start of each semi-structured interview, students were briefed on the purpose of the study and 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; 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. Figure 9 is representation of the interview's organization, and highlights which research questions correspond to which sections of the interview.

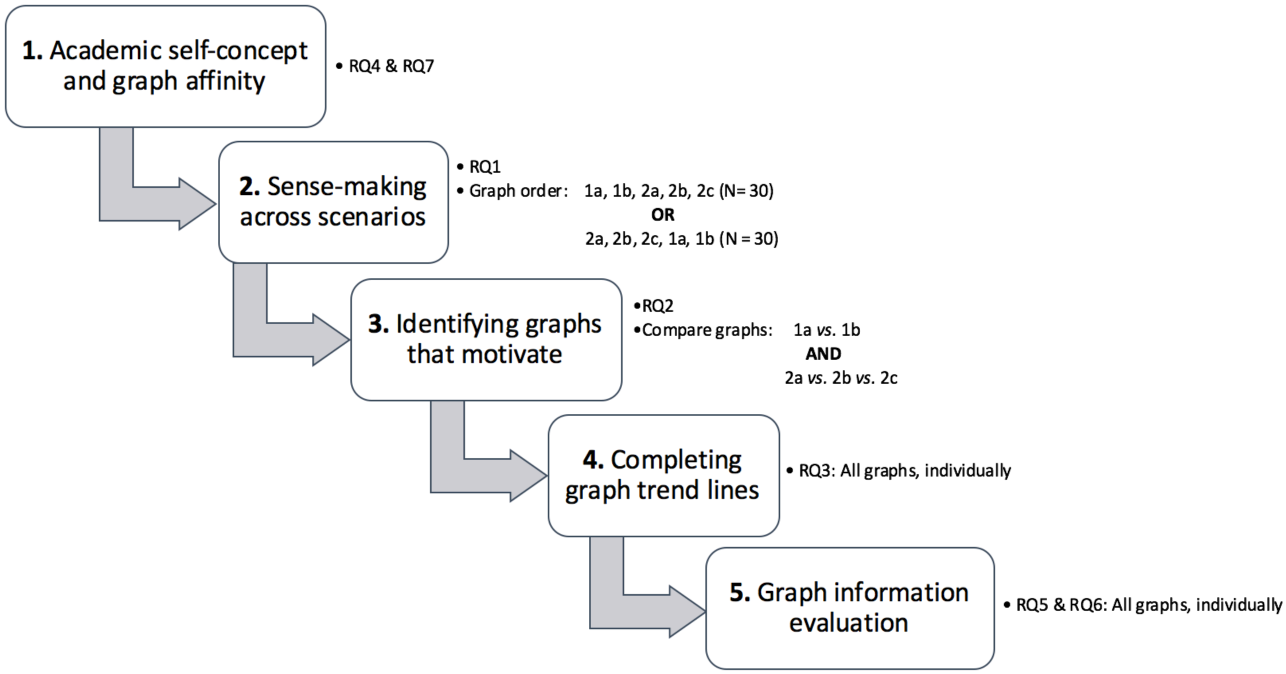


Figure 9. Semi-structured interview organization and corresponding research questions

Section 1: Academic self-concept and graph affinity (RQ4 & RQ7). At the start of the interview, participants were asked to define themselves as "students" and describe what it meant to be that sort of student. For example, students who described themselves as "hard working" would be promoted to describe what it means to be "hard working". Students were then asked to recall and describe moments when they were sure they had performed poorly in a course, and moments when they were sure they performed well in a course.

At the end of the interview, students were asked which graph they felt most closely represented them as students. After choosing a graph, students were asked explain their answers. This question assessed whether or not students gave answers that reflected the answers they gave for the first question and served as a proxy for students' academic self-efficacy, as well as how important comparisons were to them. A student could, for example, choose an upward trending graph that did not have comparison information. Depending on their stated reasons, their choice could signal that they had high academic self-efficacy, and were not interested in comparing their performance to the group (which would also imply a mastery orientation to learning). If a student chose the divergent comparative graph, they would likely have reasons differing from students who chose upward trending graphs.

Section 2: Sense-making across scenarios (RQ1). Section two of the interview began by asking students to consider a hypothetical course they would likely take in the future, and keep it in mind while they examined subsequent lines graphs. This contextualized the interview. Students in wave two were also asked what would motivate them to accomplish their stated goals. This question was added after analyzing wave one transcripts; it was included to provide additional context to students' subsequent answers. Once a course was chosen, students were presented with graphs visualizing their performance in that course.

Rationale for using a hypothetical course. Students were prompted to think about a hypothetical course for two reasons. First, it allowed the interviews to stay consistent across waves. Students from wave one 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 reasons, which allow for the results to speak to more than one academic domain.

Hypothetical courses chosen. Given the above hypothetical situation, students chose courses ranging from math courses, to courses in the humanities. Figure 10, below, provides an overview of courses chosen, with the blue bar indicating the number of students who chose a course in a given field, and the green bar representing specific different courses within that field; 12 students, for example, chose a science course, and four different types of science courses were chosen (e.g., biology, chemistry, etc.).

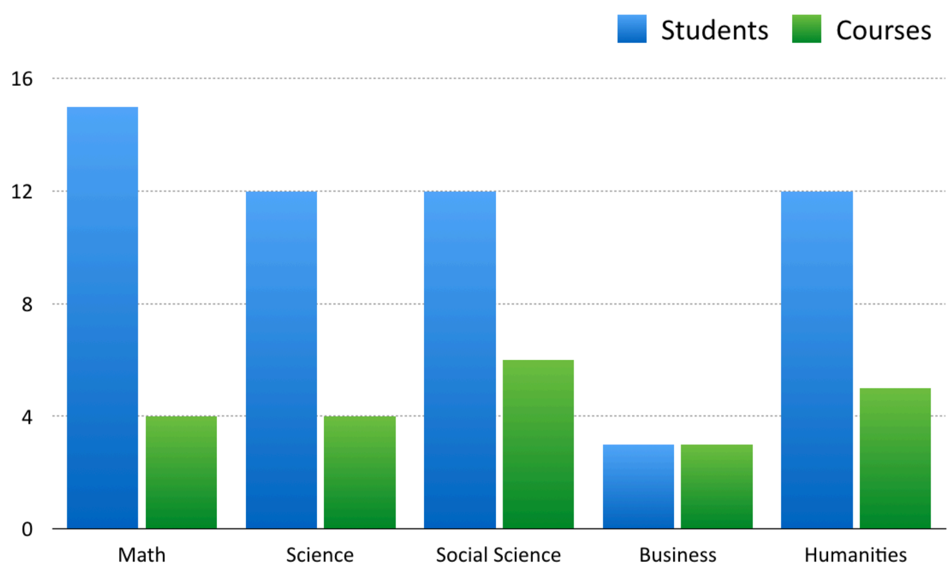


Figure 10. Students' course selection (blue), and number of courses within that field (green)

Graph order. Once students had a course in mind, and explained their reasons for choosing it, they were presented with one of five graphs to examine. Before any questions were asked, students were given approximately one minute to examine each graph, and were instructed to signal the interviewer once they were ready to answer questions.

Graphs depicting individual information were always shown first, since it was determined that it would be impossible to "un-see" comparative information once it was presented; graphs were presented in one of two possible orders (Figure 11):

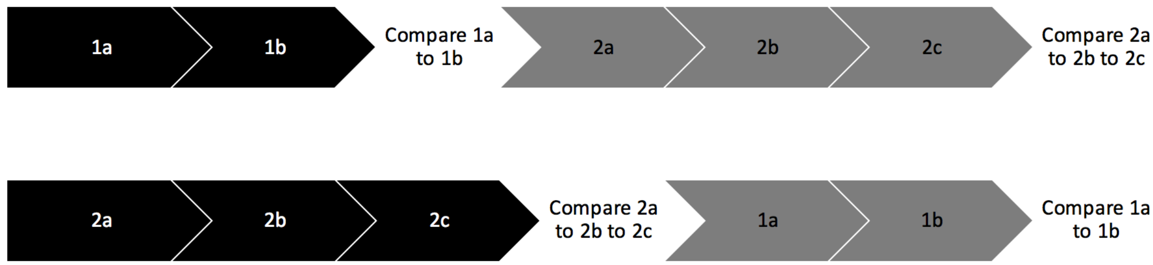


Figure 11. Order 1 (top); Order 2 (bottom)

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 also 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.

Sense-making prompts. 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.

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 a 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 as a reminder of the hypothetical course they would likely take in the future.

Section 3: Identifying graphs that motivate (RQ2). After students answered questions for each of the upward or downward trending graph, 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 re-examine each of the graphs before they chose the most motivating one. Once they selected it, they were asked to explain their choice.

Section 4: 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.

Section 5: Graph information evaluation (RQ5 & RQ6). Students were asked if the information in any of the graphs was particularly helpful, or particularly unhelpful. Helpfulness was chosen as a prompt in order to elicit a broad range of answers which could include help-seeking, self-regulated learning, etc. The final question of the interview asked students to list information they might want to see visualized in a graph if they could have access to any academic information.

Coding Scheme

Deductive coding. Since the study's primary focus is on understanding how students make sense of visualizations of academic performance from a *motivational* perspective, an *a priori* coding scheme was developed using the major constructs posited by Achievement Goal Theory (Elliot, 2005; AGT, Elliot & McGregor, 2001) and Expectancy-Value Theory (EVT, Eccles & Wigfield, 2002; Wigfield & Cambria, 2010; Wigfield & Eccles, 2000). This enabled the deductive coding of interview transcripts; each construct (e.g., mastery, in AGT) was given a code.

In accordance with AGT, three major codes were developed which 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). It should be noted that the code of "performance" was added after analysis of transcript segments 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 also developed utilizing the major EVT constructs of: expectancy, attainment-value, intrinsic-value, utility-value, and cost. The language students used while examining the graphs and answering questions was compared against survey items utilized in Eccles's (1993) study (though math is not emphasized in this study).

Codes were applied to interview transcripts of sections two through four, 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, below.

Table 2. Coding scheme

Construct	Theory	Code	Survey Example	Interview Example
Mastery	AGT	M	“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	P	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	AGT	PA	“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	AGT	PV	“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”
Expectancy	EVT	E		“All my courses I expect to get an A. I'm striving for A. But I guess I'm okay with a B, or something, or C.”
Attainment-Value	EVT	AV	“For me, being good at math is (not at all important, very important)”	“I need to learn how to do those things in order to progress in the field that I want to study and eventually work in.”
Intrinsic-Value	EVT	IV	“Compared to most of your activities how important is it for you to be good in math?”	“I wanna begin to learn the culture of sign language. I think it's really interesting.”
Utility-Value	EVT	UV	“In general, how useful is what you learn in math?”	“If I feel like it's definitely going to affect my circumstances with dental school, 'cause that is my future plan, I generally try to do a lot harder on those and focus on those.”
Cost	EVT	C	“How much does the amount of time you spend on math keep you from doing other things you would like to?”	“I think it takes more time 'cause it gets more stressful, more hard, more challenging, I suppose.”

Inductive coding. A general inductive approach (Thomas, 2006) was used to evaluate transcript segments relating to how students relate visualized academic performance to their own academic self-efficacy (RQ4 & RQ7), and to capture their evaluations of the information visualized by the graphs used (RQ5 & RQ6). These responses, were not necessarily tied to students' motivation, enabling them to be coded inductively. Information seeking and graph feature evaluation emerged as two themes. Table 3 provides more detailed information, including codes and examples from the interview which emerged after analysis.

Table 3. Inductive codes

Theme	Codes	Description	Interview Example
Information Seeking	Prediction of grade	The desire for the graph to predict students' future grades based on previous information.	"It'd be helpful to see what would happen at the end, even though you can see where the graph is going."
	Possible resources	Wishing that the graph also provided more information on which resources students could use to improve their grades	"…[what] I'm having the most trouble with maybe…so that I can go back and…try to study that a little bit more to seek help"
	Granular grade information	Wanting a more granular breakdown of a given grade (e.g., exam scores, assignment scores, etc.)	"…perhaps what I got wrong and why I got it wrong, and in assignments the same thing, why I got it wrong"
	Nothing	Stating that the information shown was sufficient, no stated recommendations for more information	"Nope. I think this is helpful."
Graph Features	Class average	Referencing the class average as wither helpful/unhelpful	" I like how you showed the class averages for these two... hey tell me better with predicting the end outcome based on seeing the average."
	Study strategies	Stating that a graph evoked thoughts about study strategies, coded as helpful when it emerged	"I can help myself to prioritize and change some behaviors to move forward in the future."
	Progression	The helpful/unhelpfulness of the graph depicting grades on a week by week basis.	"[the graph] tells me that I can move forward and I can do well in the class…"
	Design	Affinity for the design features of the graph (e.g., keys, labels, etc.)	"The key was very organized and showed which was my average, the class average, which lines to look at."

Results

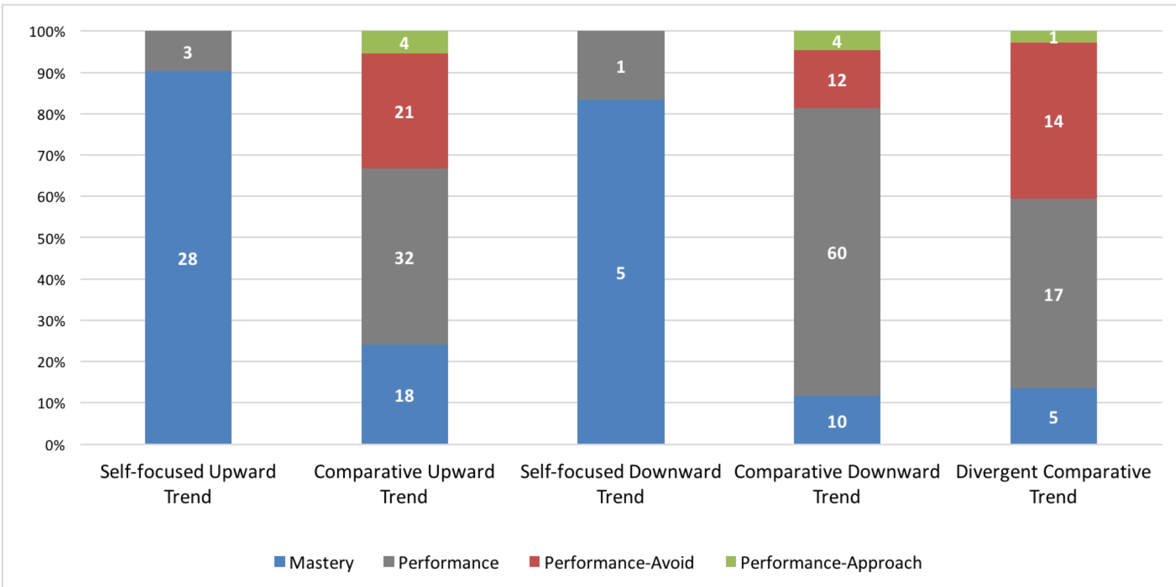
Results are organized into five sections, each encompassing a specific set of research questions. The first section presents the results of: 1) students' sense-making around their comprehension of the five graphs used, 2) how they would communicate the affordances of the graph to their peers, 3) the salient features they noticed within each graph, and 4) the accuracy of their comprehension of where they began the term relative to the comparative graphs, i.e., whether or not students thought they started with the same grade. Each sub-section presents the results of both AGT and EVT deductive coding.

The second section presents the results of which graphs students found more motivating, while the third presents the results of students' predictions of their future performance in the hypothetical course. The fourth section summarizes students' evaluations of the information afforded by each graph; the final section organizes students' responses to which graph they had an affinity towards, and casts that information against responses assessing their self-efficacy at the beginning of the interview.

Sense-making Across Scenarios (RQ1)

Figure 12 (below) provides a general overview of AGT and EVT 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 non-dimensional performance affordances 3 times (approximately 10% of the time).

As can be seen below, AGT codes were observed at a higher rate across both graph type and interview question, indicating that students generally interpreted graphs in line with AGT constructs. They did not interpret graphs via EVT nearly as often. The following sections break down the figure below into its three constituent parts: comprehension, salience, and graph communication.



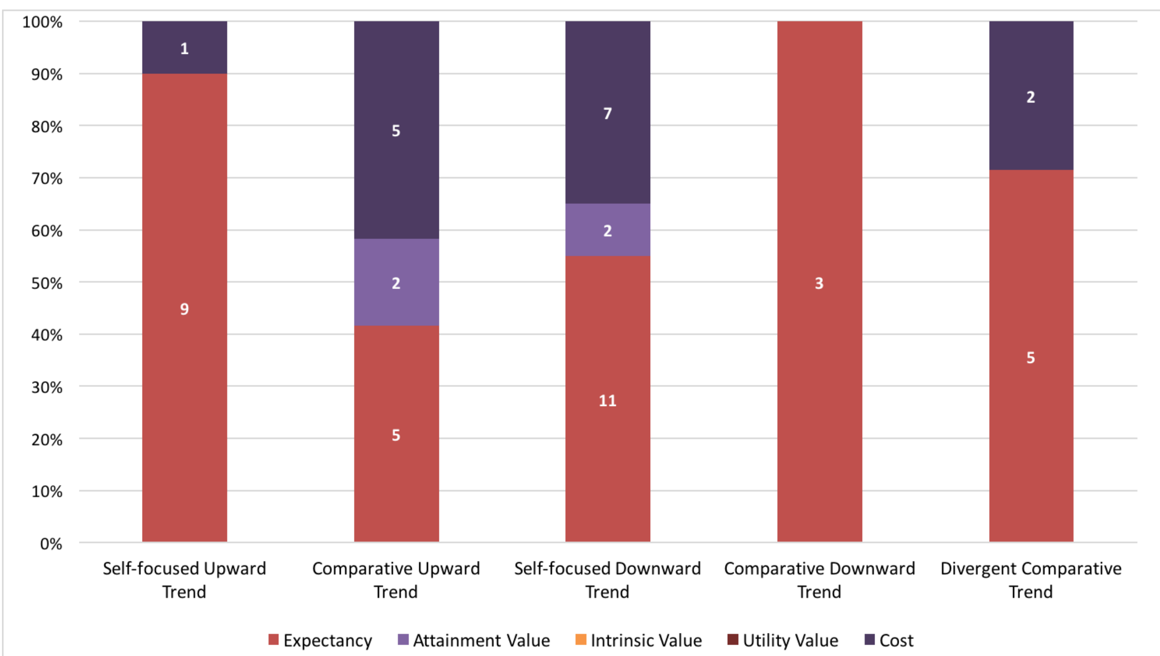


Figure 12. Overview of AGT codes (top) and EVT codes (bottom) across comprehension, salience, and communicating graph information interpretations

Comprehension. From an AGT perspective, the self-focused graphs yielded more mastery statements (Figure 13), which one would expect given that mastery is an inward looking construct; the graph design does not show any comparative information.

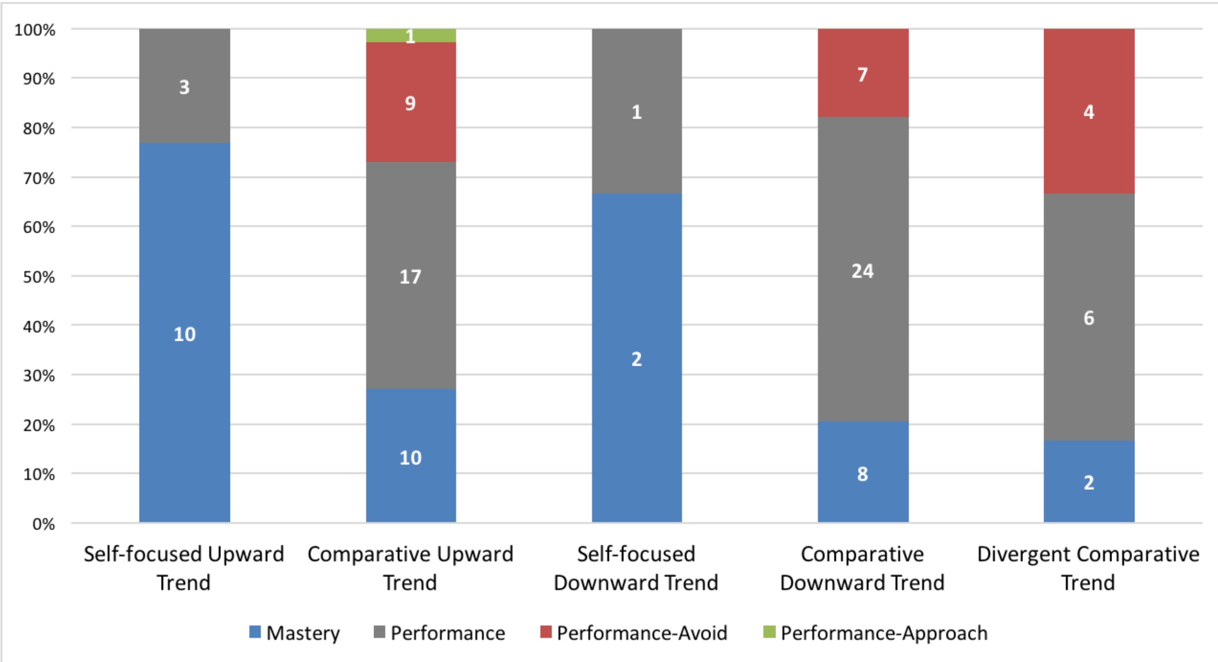


Figure 13. Overview of AGT coded segments as students answered: "How are you doing in the course?"

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, non-dimensional performance (i.e., is neither approach nor avoid) statements were made the more often, indicating that students did interpret performance aspects of the graph. Performance-approach, however, is absent from all but one graph type (comparative upward), which yielded one code. This suggests that performance-avoid is more likely to be interpreted when a graph shows a comparison.

EVT coded statements were not as prevalent (Figure 14); only 15 statements were coded as being EVT-related across all five graph types. When EVT statements were found, however, they tended to be tied to students' expectancies. This concurs with the design of the graph, which is set against time, and may influence students' expectancies relative to their success and/or failure in the hypothetical course. Cost was also coded 5 times across students and graphs, indicating that students also thought about what succeeding or failing might cost them over the course.

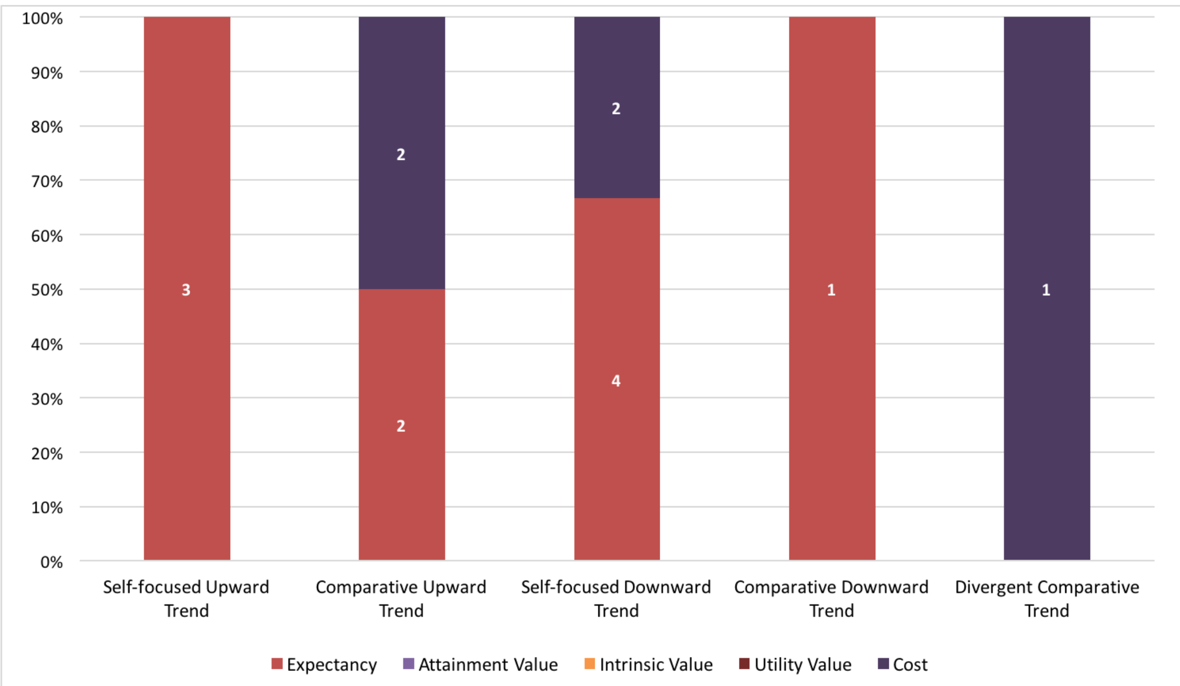


Figure 14. Overview of EVT coded segments as students answered: "How are you doing in the course?"

Communicating graph information. As with students' answers regarding how they understood their progress in the course, self-focused graphs yielded more explanations that parallel AGT mastery language when presented with self-focused graphs, and more performance explanations when presented with comparative graphs. 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 non-dimensional performance (Figure 15).

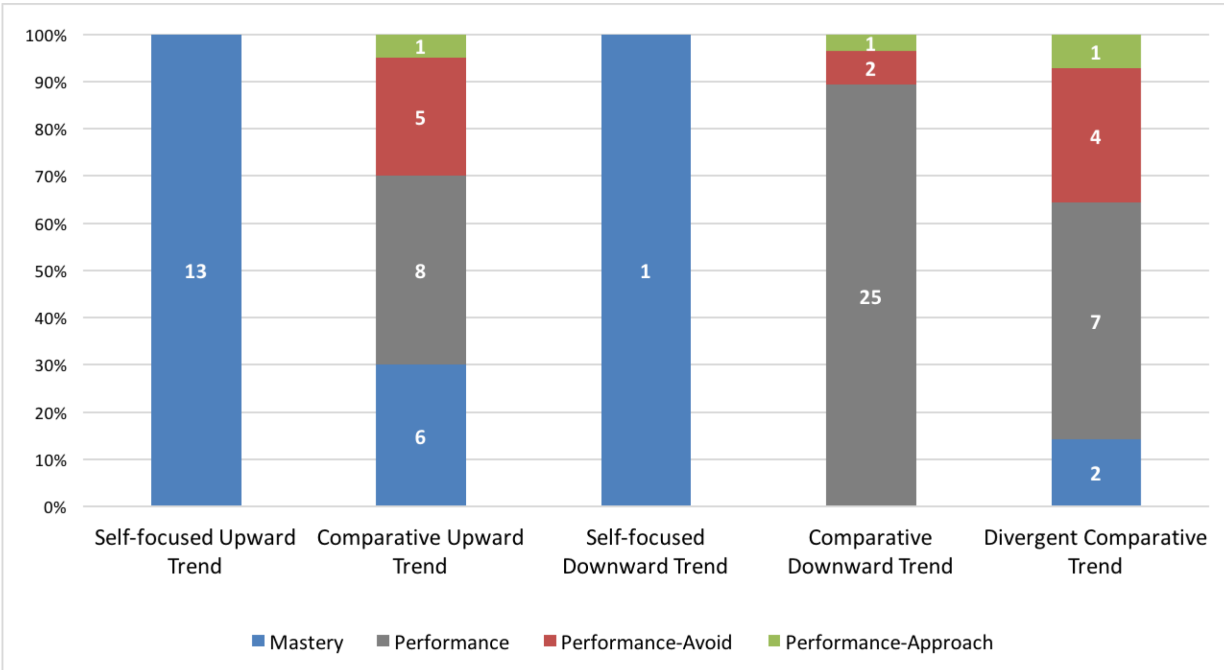


Figure 15. Overview of AGT coded segments as students answered: "How would you explain this graph to one of your fellow students/peers?"

Similar to the comprehension section of the interview, relatively few (17) statements were coded as having EVT interpretative content (Figure 16). Of these, the majority were expectancy statements, indicating students would most often communicate a graph's affordances to others by suggesting an imperative to improve on the presented situation. The exception to this was the self-focused downward trending graph, which yielded one attainment statement, and two cost statements. As with comprehension, cost was the second most coded statement, suggesting that students tie expectancies to the cost of achieving an expected outcome.

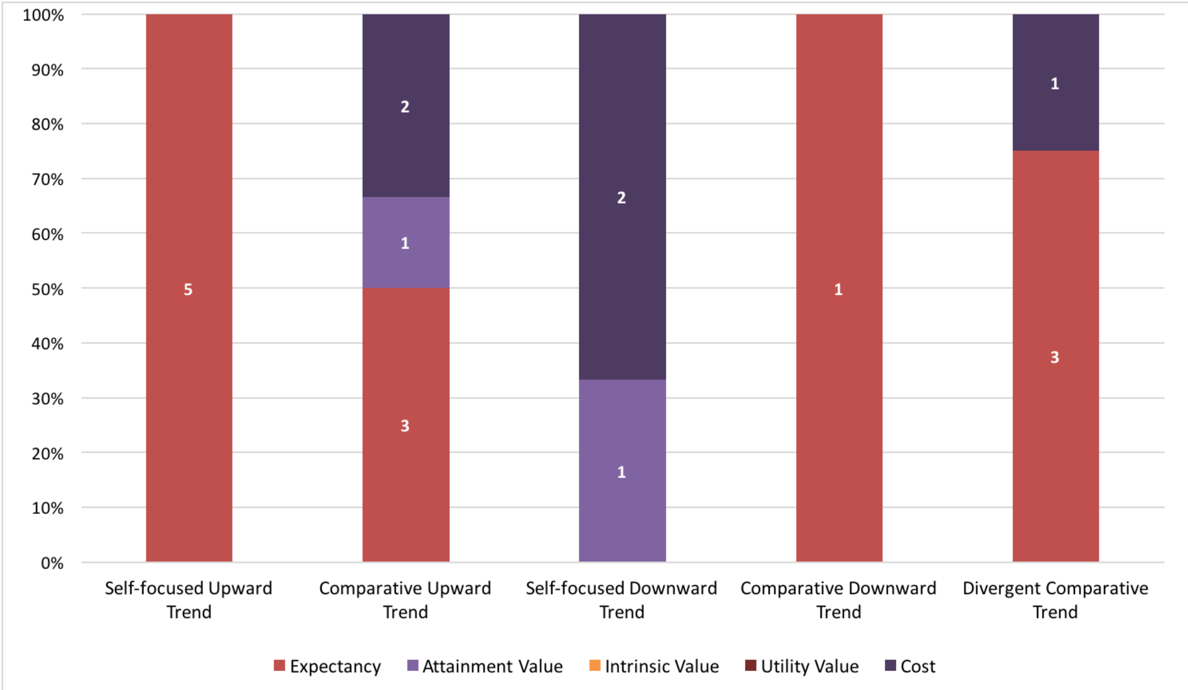


Figure 16. Overview of EVT coded segments as students answered:

"How would you explain this graph to one of your fellow students/peers?"

Salient features. In accordance with other sense-making prompts, students used mastery language when they commented on the most salient features of the self-focused graphs they were presented. This suggests that non-comparative (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 17).

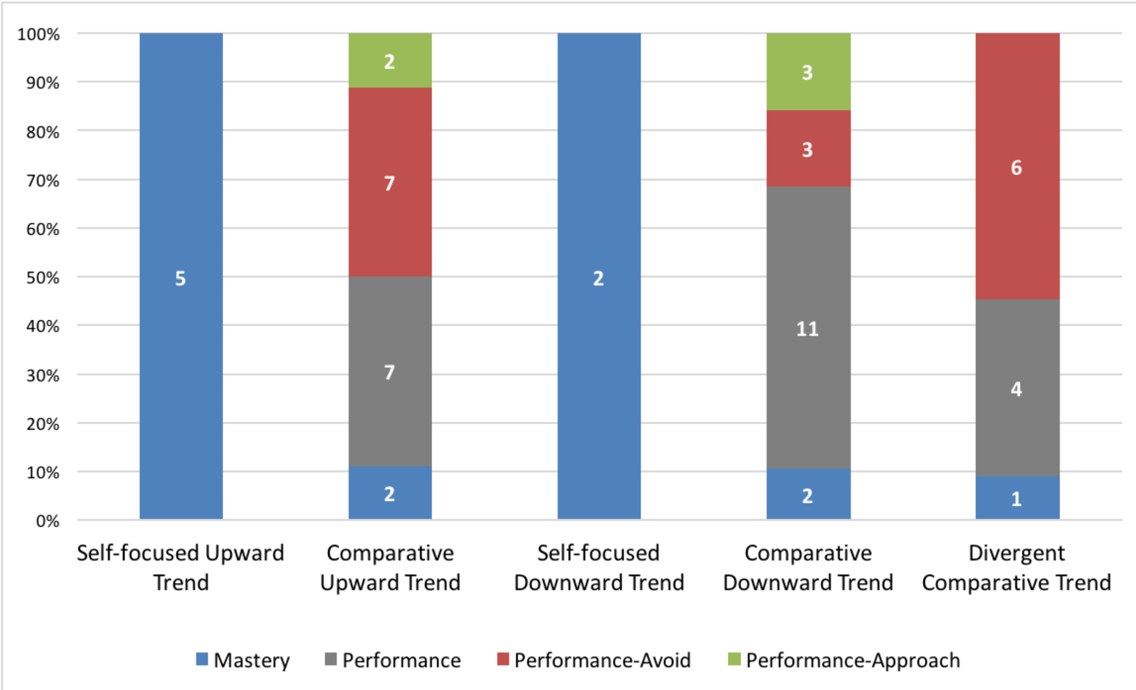


Figure 17. Overview of AGT coded segments as students answered: "What was the first thing you noticed about the graph?"

A total of 18 statements were coded with EVT language (Figure 18). Of these, the majority (11) were expectancy statements, with cost (5) coming in second. This is unsurprising, since it is unlikely that students would immediately notice features that align with EVT constructs, given that the affordances of the graphs are to communicate performance. When language consistent with EVT was found, however, it contained statements tied to students' expectancies for success given the presented scenario, or what it would cost them to succeed. Two students mentioned why it was impotent for them to succeed given the circumstances (attainment).

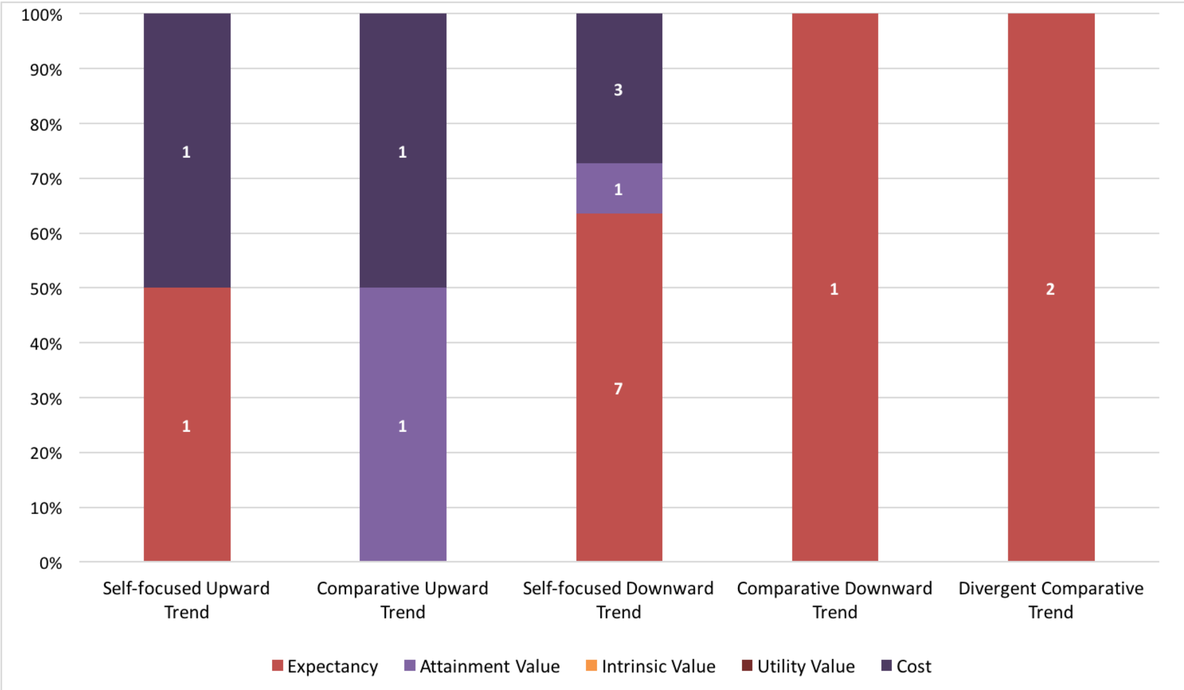


Figure 18. Overview of EVT coded segments as students answered:

"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 frequently (12%, n = 7).

A total of 162 codes were applied to students' reasons for choosing the most motivating graph using the AGT coding scheme. Figure 19 (below) 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' responses did not yield any EVT-related language.

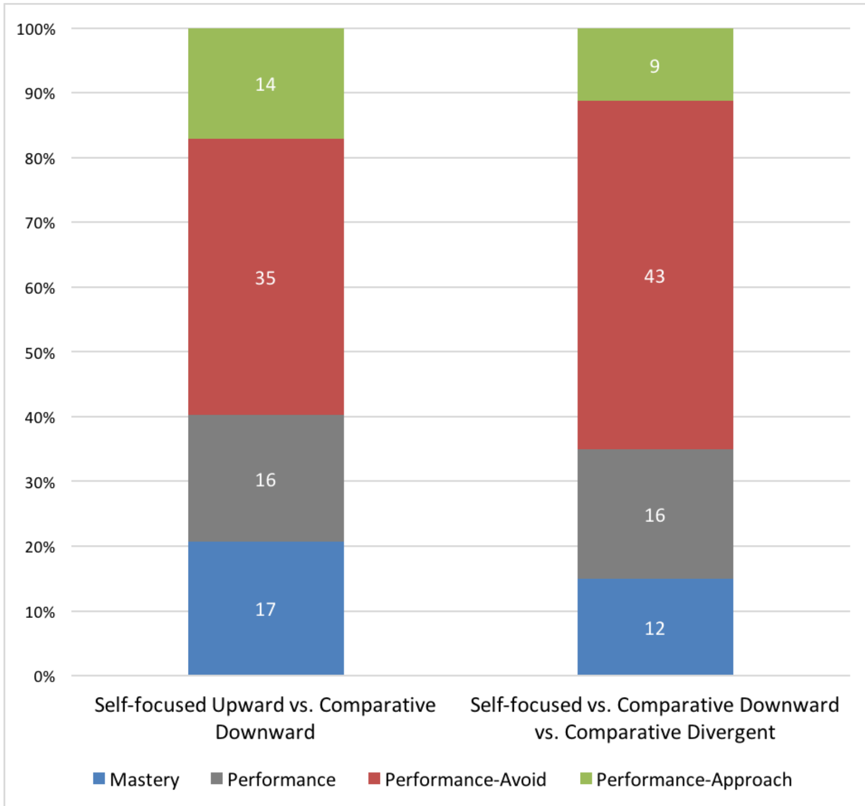


Figure 19. Overview of AGT coded segments as students chose most motivating graph.

Completing Graph Trend Lines (RQ3)

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 end points of the drawn lines were then examined and linked numerical values (a line ending at the very top of the graph by week 14, for example, would be coded 100%, indicating that a student believed they 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. Analysis indicated that there were no detectable differences across graph type. On average, each student predicted that they 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, predict that they would do worse before they would do better for two graphs: self-focused downward trending and comparative divergent downward trending. (See Table 4 for summary statistics of student predictions).

Table 4. Summary statistics of differences across graph type

	Mean	SD	Min	Max
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

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 20, with each bar corresponding to a particular graph (e.g., 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 (4 times in the comparative upward trending graph, and once in the divergent graph). More details, including plotted student predictions and examples of phrases used, is presented below.

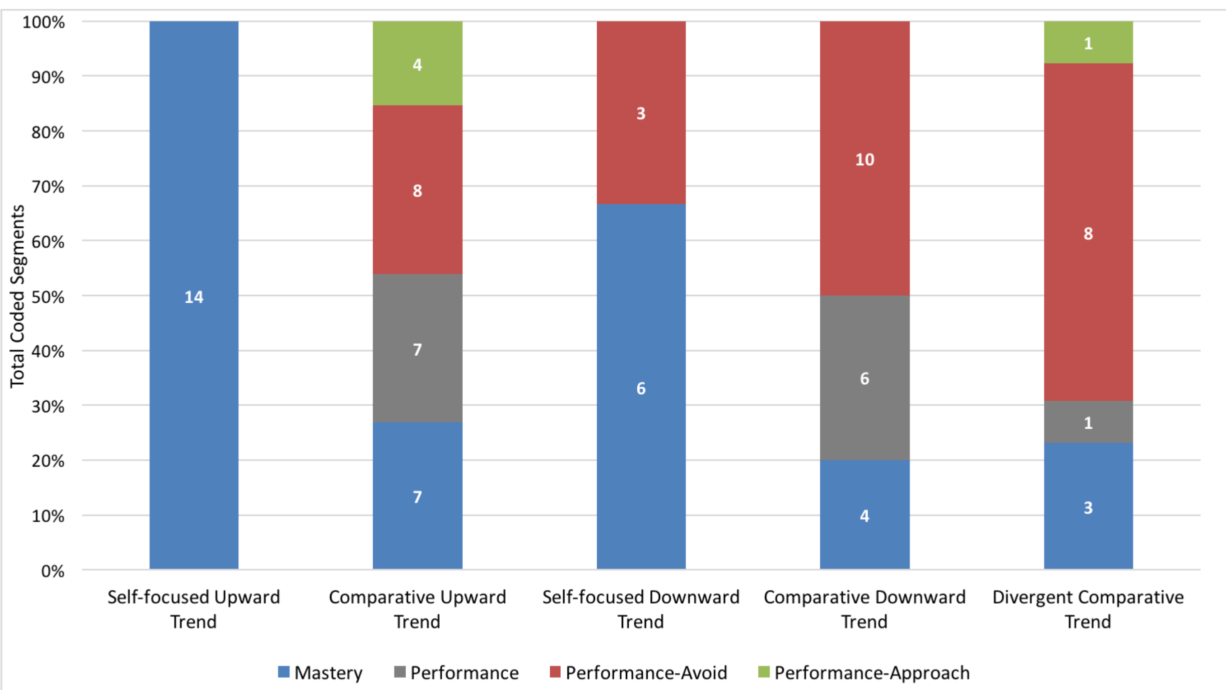


Figure 20. Overview of coded segments by graph type and AGT codes

Graph 1a: Self-focused & upward trending. Figure 21 shows the range of predictions for the self-focused and upward trending graph. Language used while drawing these predictions was limited to mastery statements such as:

> 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)
>
> I guess I just assumed because it was increasing as the weeks went by, that it would continue to do that, because I'm just building upon a good grade with better assignments and scores. (Female 2)
>
> I guess since it was increasing already, I guess I was more motivated to really get a good grade in the course so…(Female 3)

Graph 1b: Comparative & upward trending. Figure 22 shows the range of predictions for the comparative and upward trending graph. Students' interpretations ranged across each of the four possible AGT codes. Examples included:

*Mastery***.** Mastery examples included:

> And this graph made me realize that I actually can learn the information, because since from week one to week seven, I've learned almost 20% more than... I mean, performance is 20% higher than it was before, so it shows that I can do it, so why can't I learn more? (Male 1)
>
> Because, just knowing myself, I think I won't have an all-of-a-sudden drop or decrease in performance because I like to stay consistent. (Male 2)
>
> 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)

*Performance***.** Performance examples included:

> It's like win-win. I'm up there with everybody else but I'm also doing my best. (Female 5)
>
> Comparing this to the class average, I know that I'm gonna do a lot better now that I know that the class, [average] (Male 3)

Performance-Approach. Performance-approach examples included:

> It would make me wanna be above average, if not at average. So I'd probably try harder to get better grades than them because I know that they started off almost just like me. (Hector)
>
> 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)

Performance-Avoid. Performance-avoid examples included:

It challenges you more because you don't wanna... Well I don't wanna be below the class average (Female 6)

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)

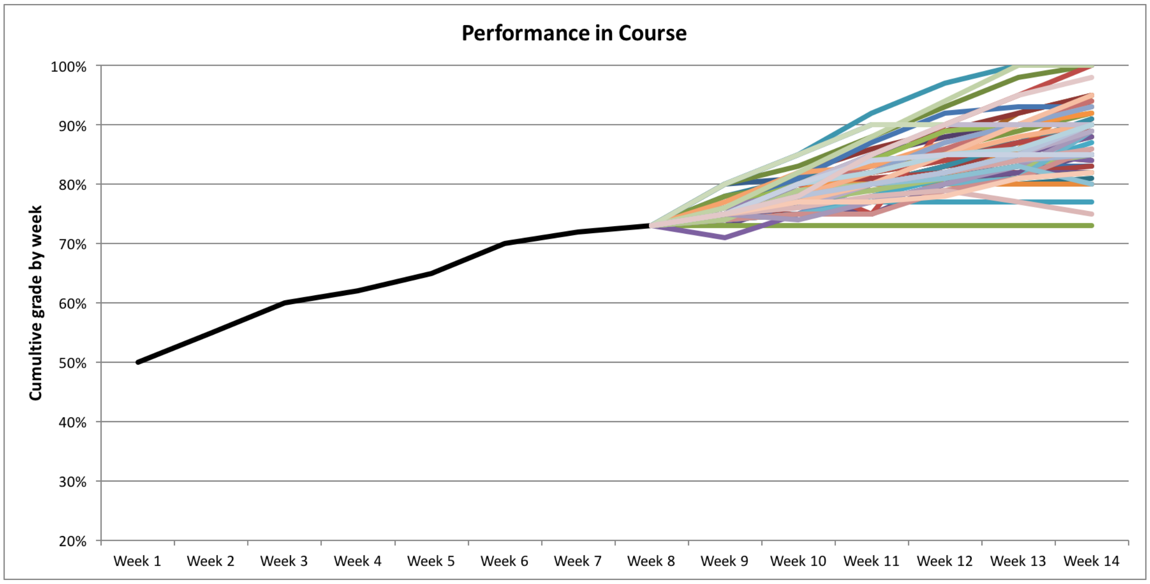


Figure 21. Students' completed trend lines for self-focused and upward trending graph

(Week 14 *M* = 88%, Start = 73%, Min = 73%, Max = 100%)

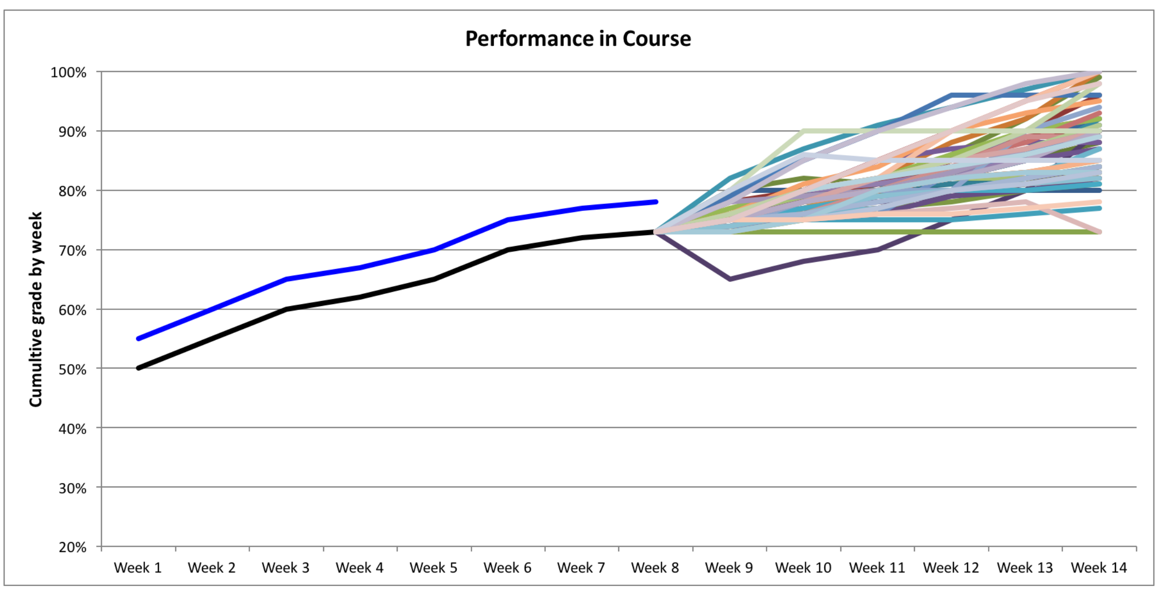


Figure 22. Students' completed trend lines for individual and upward trending graph

(Week 14 *M* = 88%, Start = 73%, Min = 73%, Max = 100%)

Graph 2a: Self-focused & downward trending. Figure 23 shows the range of predictions for the self-focused and downward trending graph. Graph 2a evoked mastery interpretations, including:

> I can, to get the highest grade that I can. But it would take a while... That's why I drew a little straight line. Little progress and then slowly increase. (Female 8)

> 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)

Graph 2b: Comparative & downward trending. Figure 24 shows the range of predictions for the comparative and downward trending graph. Students responses evoked both mastery interpretations as well as performance and performance-avoid interpretations.

Mastery. Mastery statements included:

> 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)

> So my average will be the same every time I look at a graph, rather than worrying about the class average or anything like that. (Male 4)

Performance. Performance statements included:

> 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. (Anthony)

> I couldn't really figure out any certain way to correlate that with the class' average. (Male 5)

Performance-Avoid. Performance-avoid statements included:

> 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)

> I did this one because me personally, if I saw that I was doing below average compared to my class, I would have something to prove to myself in order to do better. (Female 11)

Graph 2c: Comparative & divergent. Figure 25 shows the range of predictions for the comparative and divergent trending graph. This graph yielded both interpretations across each AGT construct.

*Mastery***.** Mastery interpretations included:

> 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 just think that... I just feel like I'll do what I have to do to get the content done, so I can get the grade that I want, (Male 6)

Performance. Performance interpretations included:

> I feel like the class average is gonna motivate me to work harder. (Female 12)

*Performance-Approach***.** Performance-Approach interpretations included:

> I'm gonna do better than the class average. (Male 7)
>
> Again, probably seeing everybody else do better. I wanna do better. (Female 13)

Performance-Avoid. Performance-avoid interpretations included:

> Because not only for this one is the rest of the class doing better, but I'm doing worse. So I think that that would kind of make me feel behind almost and kind of motivate me to do better. (Briana)

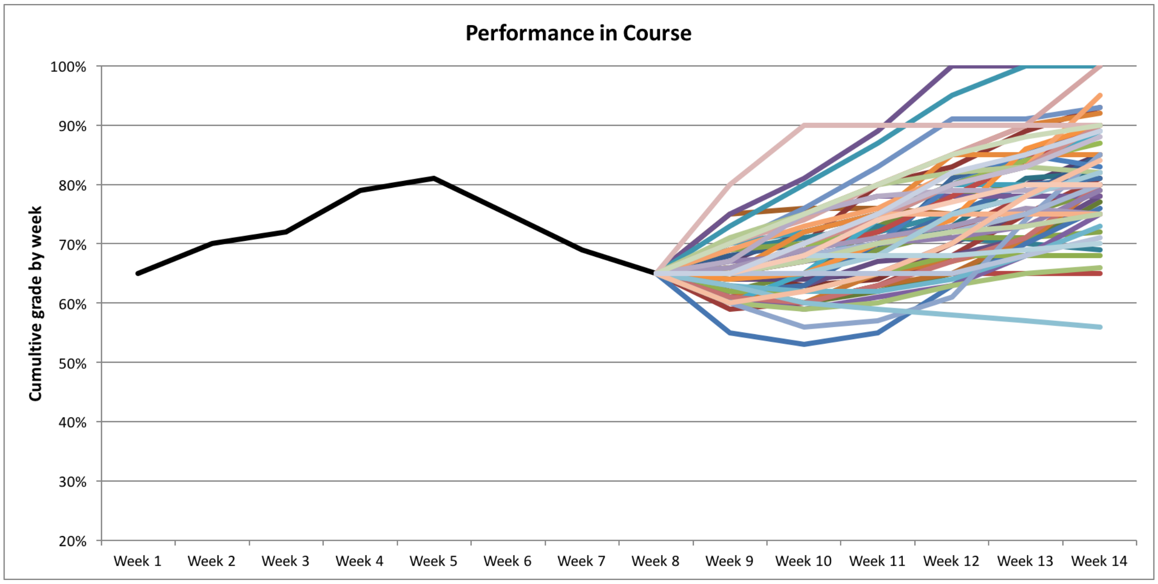


Figure 23. Students' completed trend lines for individual and upward trending graph

(Week 14 *M* = 82%, Start = 65%, Min = 56%, Max = 100%)

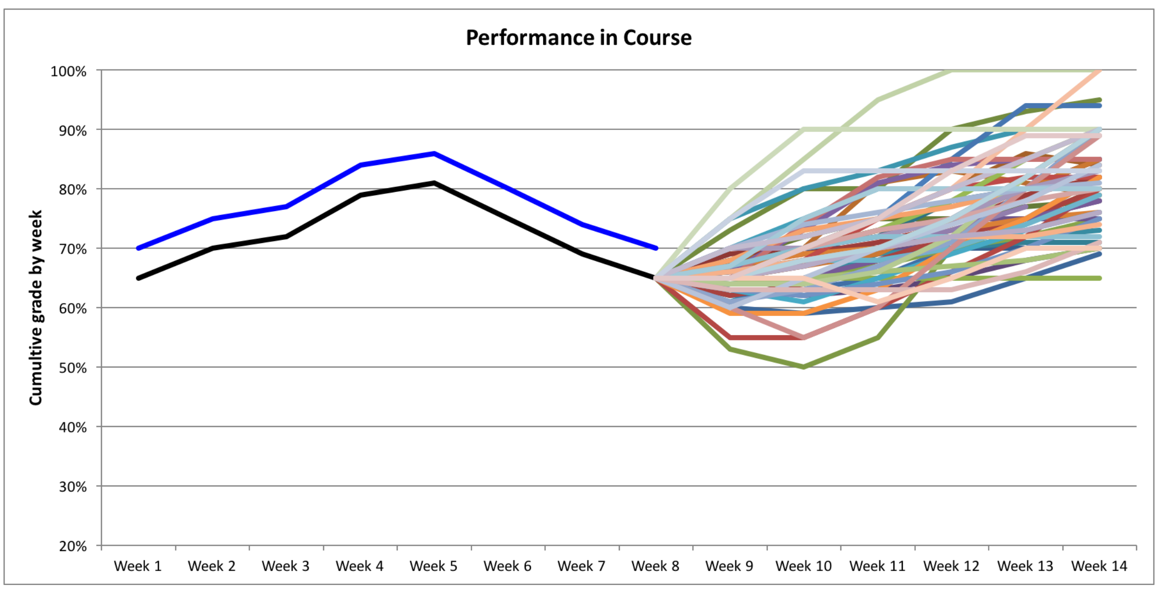


Figure 24. Students' completed trend lines for individual and upward trending graph

(Week 14 *M* = 81%, Start = 65%, Min = 65%, Max = 100%)

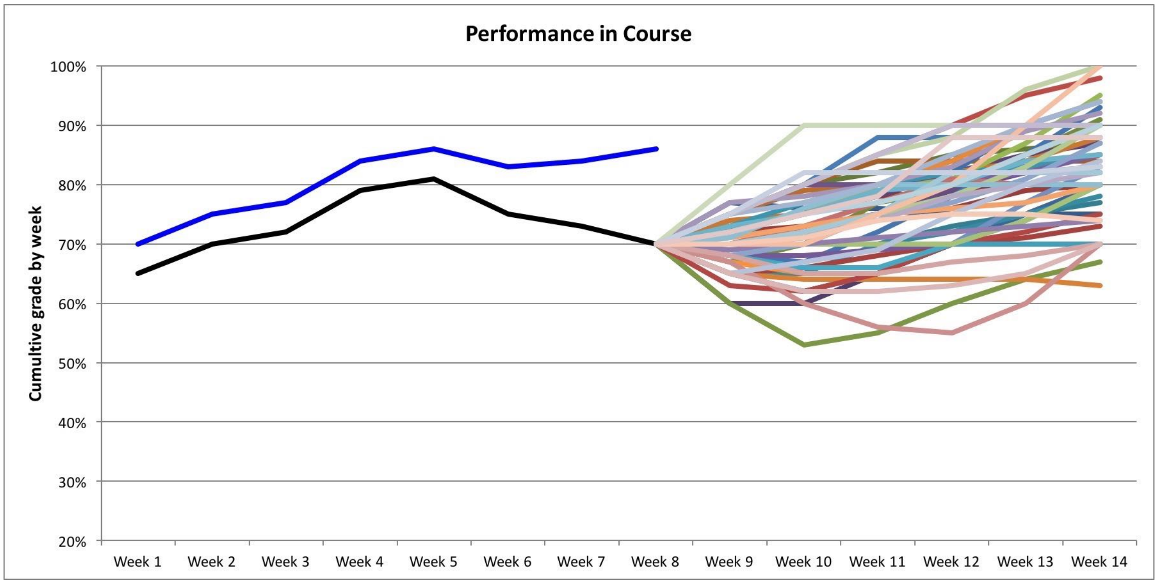


Figure 25. Students' completed trend lines for individual and upward trending graph

(Week 14 *M* = 83%, Start = 65%, Min = 63%, Max = 100%)

Graph Information Evaluation (RQ5 & RQ6)

Students were asked to identify helpful or unhelpful graph features (RQ5), and also mention additional information they would like to see in future graph designs (RQ6). Results were coded inductively, and organized around common themes (i.e., students mentioning the class average as helpful).

Helpful vs. unhelpful information (RQ5). When asked to consider what information students found helpful (or unhelpful), the following themes emerged: the class average, the design of the graph, the "week by week" nature of the graph, and the fact that it helped them think through possible study strategies.

Overall, students were reluctant to mention graph features that they considered unhelpful—only 10% of the students interviewed mentioned "unhelpful" features. When commenting on helpfulness, the vast majority of students mentioned the class average as being the most helpful feature of the graph (Figure 26).

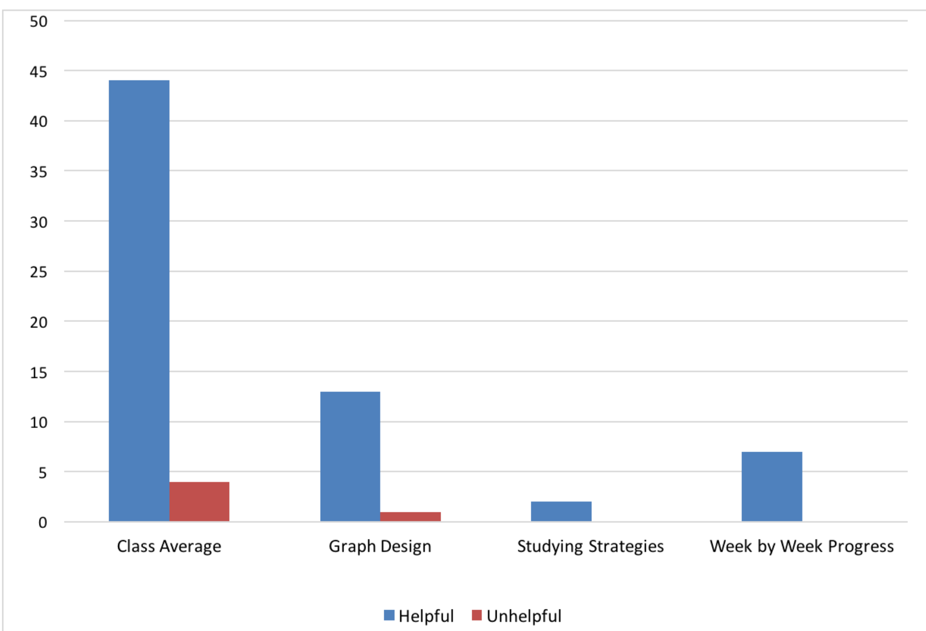


Figure 26. Overview of identified helpful/unhelpful graph features.

Additional information (RQ6). When asked to suggest additional information that might be “helpful" to have, the following codes emerged: 1) possible resources to help (e.g., exam information, syllabus information, etc.); 2) predictions of their grade; 3) nothing; 4) more granular grade information (e.g., assignment breakdown, etc.).

Overall, students communicated that the graphs showed sufficient information, and either did not suggest additional information or said that the information present was sufficiently helpful. Roughly one-sixth of the students (10) wanted to have more granular grade information, while 6 students wished that the graph showed possible resources for them to improve their grade (Figure 27).

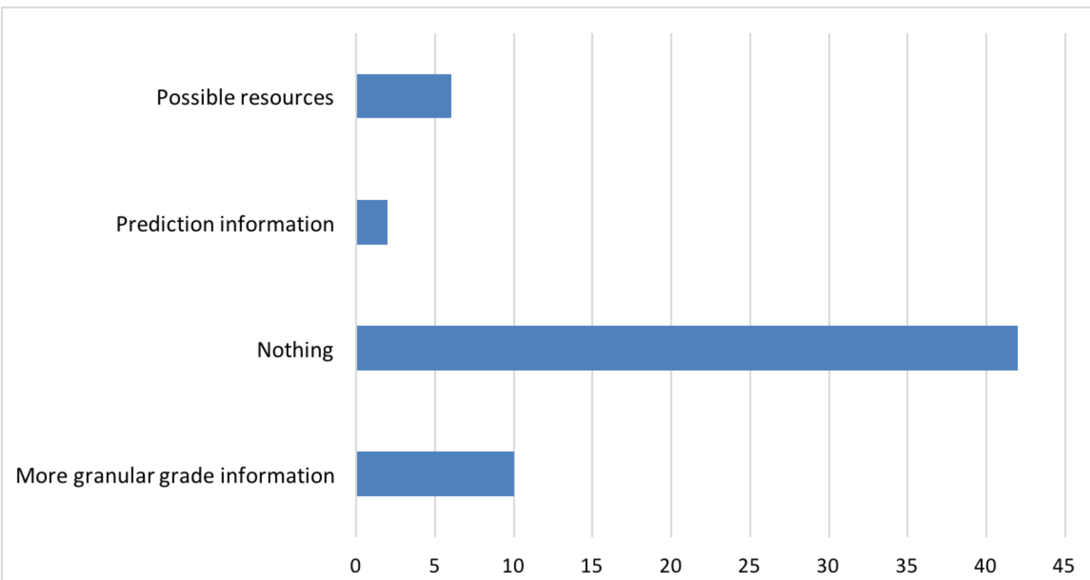


Figure 27. Overview of suggested additional information.

Academic Self-concept and Graph Affinity (RQ4 & RQ7)

Choosing a representative graph (RQ7). At the end of the interview students were asked to choose a graph that “best represented the type of student they were.” Figure 28, below, illustrates a breakdown of their responses. Over half of the students (58%, n = 34), chose the self-focused, upward trending graph. This result, interestingly, is in contrast to the graph students chose as more motivating (RQ2), where the majority chose graphs with comparative information.

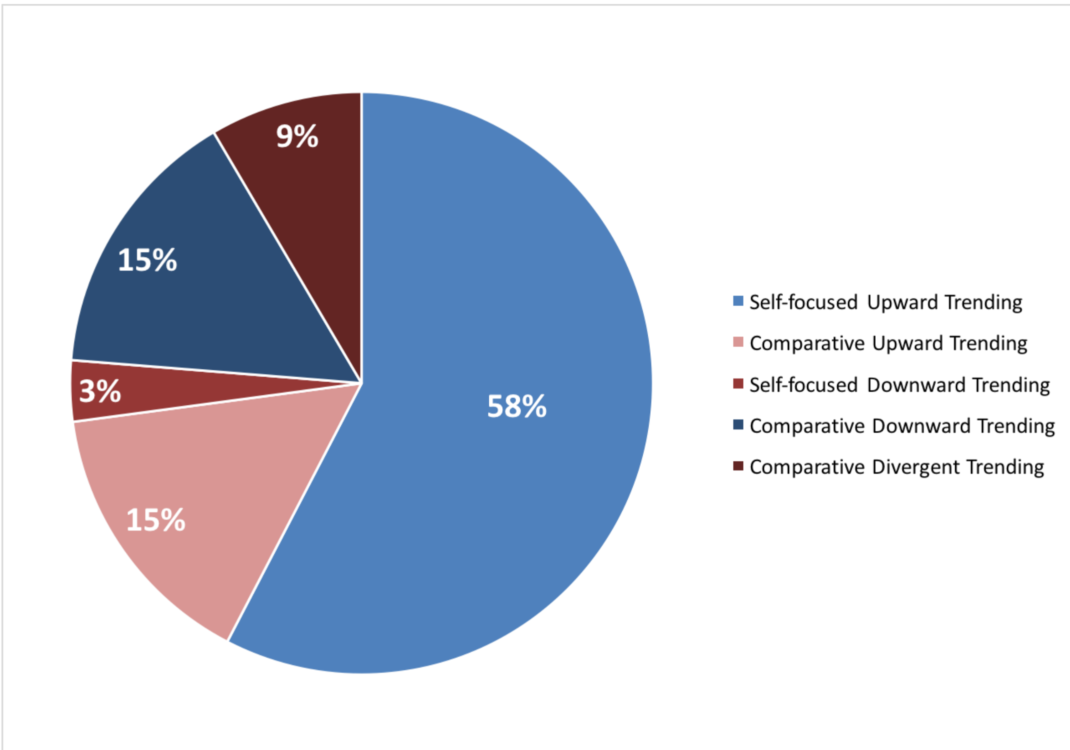


Figure 28. Breakdown of students’ choices regarding graph affinity

Discussion

Learning analytics applications 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 towards more complex thinking about how the task will be—or has been—accomplished. This added knowledge also has the potential to motivate students in new and interesting ways, and lead them to make choices unknown to them before, although it may also result in maladaptive motivational consequences, which will be discussed subsequently.

All learning analytics applications also have the potential to interfere with learners' established processes and workflows for learning. This possibility was investigated by studying a necessary component of learning analytics applications: the representations they use to communicate actionable 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, whose constructs captured the salient responses to graphs with comparative information. These results suggest the mastery/performance distinction within AGT maps onto representations which are self-focused and comparative, while also allowing room for EVT constructs to be evoked during sense-making.

Students' moreover, found that comparative graphs designed with performance information affordances were "more motivating." Despite this, more students chose an self-focused, upward trending graph as one that was most representative of the type of student they are. This represents a tension between what students find motivating, and how they identify themselves as students.

When asked to compare graphs with self-focused vs. comparative information in order to determine which they find “more motivating,” students’ explained their answers in ways more consistent with AGT than EVT, suggesting that the information environment that emerges through learning analytics applications—if designed with comparisons and with self-focused information—evoke 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, is it 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 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’s displaying some student information at the expense of other work), it is nonetheless important to study the effects of this feedback.

Thus, the narrowing of students’ choices over what they see can be justified through meticulous design that is evaluated for its efficacy—or that at least is the assumption. Doing so “unpacks” the choices that dictate what information is deemed important and what information is deemed unimportant. This is important because such decisions are not idle ones, but are instead the result of various design elements chosen by researchers; the true knowledge affordances of any learning analytics application (i.e., what it is possible for the user 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 the researches 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.

Chapter 4: Measuring Students' Motivational Predispositions Towards Academic Information Visualizations

Using representations to communicate academic information to students is not new. The letter "A," for example, has been used to represent excellent work in the American educational system for over a hundred years. As a given representation becomes ubiquitous (e.g., basing grades on a 0-100 score), its intended meaning becomes established—students understand what it means to get a 30% on an exam, for example. As new representations are introduced in educational settings, however, their intended (and unintended) meanings are less straight forward, and require study in order to better understand how they are interpreted by students.

While the various interpretive modalities students use within education can (and should) be studied, the role representations play when it comes to their academic motivation is particularly important because motivation has been linked to how students engage with types of courses (Perez et al., 2014); help-seeking behaviors (Karabenick, 2004); cheating behaviors (Murdock & Anderman, 2006); and retention (Eaton & Bean, 1995), among others. In short, motivation *always* plays a role in learning, and there is thus great value in studying how motivation relates to learning (Schunk, Pintrich, & Meece, 1996).

Although traditional learning environments still lean heavily on standard representations of achievement (e.g., letter grades), this is not the case for emerging environments, such as learning analytics applications. Due to the fact that these applications draw heavily on vast quantities of (often) disparate data sets (e.g., Krumm et al., 2014; Wise et al., 2013), learning analytics applications often make use of visualizations as a specific type of representations to communicate important information (Pardo, 2014; Siemens, 2013).

Study 1 explored how at-risk students interpreted line graphs that displayed hypothetical course achievement. Results indicated that a graphs have distinct information affordances that are “read” by students, e.g., a self-focused line graph will be interpreted through the lens of mastery. Additionally, it was found that students may still infer comparative information, even if the graph itself is not designed that way. This suggests that students may have certain affinities or predispositions that influence how they interpret visualizations.

The present study adds to Study 1 by empirically defining constructs that play a role in the interpretation of visualized academic information. It focuses on the development and validation of a survey instrument intended to measure attitudes toward various visualizations of academic information (e.g., setbacks, successes, and failures), and then uses the scales to predict outcomes of interest (described below). The proposed Motivated Information-seeking Questionnaire (MISQ), draws its inspiration from Achievement Goal Theory (AGT, Elliot, 2005; Elliot & McGregor, 2001; Midgley et al., 2000), and measures students’ affinity towards certain types of academic information in a manner that parallels AGT’s mastery, performance-approach, and performance-avoid constructs. The proposed “mastery information-seeking” (MIS), “performance-approach information-seeking” (PAIS), and “performance-avoid information-seeking” (PVIS) scales, are tested, validated, and related to non-cognitive outcomes such as students’ attributions toward their academic performance in a course, and academic outcomes of interest such as Grade Point Averages (GPA).

Hypothesized Model

The proposed motivated information-seeking questionnaire (MISQ) is an instrument designed to measure three distinct motivational orientations that drive the kind of achievement information students feel an affinity toward. I hypothesize that the constructs that are measured by the MISQ drive attitudes are parallel to—but distinct from—the constructs of Mastery, Performance-Avoid, and Performance-Approach that have been studied in the Achievement-Goal Theory literature (Elliot, 2005; Elliot & McGregor, 2001; Elliott et al., 1988; Karabenick, 2004).

This should yield a three-factor structure, consisting of Mastery Information-seeking (MIS), Performance-Approach Information-seeking (PAIS), and Performance-Avoid Information-seeking (PVIS). While Elliot et al. (2001) found support for a 2x2 model that included mastery-avoidance, it has not been frequently studied in the literature. Thus, Mastery-Avoidance is not hypothesized to play a role in the interpretation of visualizations of their academic performance, and is not included in the hypothesized factor structure of the MISQ.

Students with strong MIS will generally feel more affinity toward self-focused representations of their academic information (e.g., graphs that only show their progress in the course). PAIS and PVIS students, on the other hand, will feel more affinity toward comparative representations of their academic information; PAIS students will want to see representations that show them ahead of their peers, whereas PVIS students will want to avoid seeing representations that show them doing worse than their peers.

Hypothesis 1. Mastery Information-seeking (MIS), Performance-Approach Information-seeking (PAIS), and Performance-Avoid Information-seeking (PVIS) will be related to, but distinct from, Mastery, Performance-Avoid, and Performance-Approach that have been studied in the Achievement-Goal Theory literature.

Hypothesis 2. Students' motivated information orientation to any given representation will have adaptive or maladaptive associations with outcomes of interest, such as their academic performance. PVIS, for example, is hypothesized be positively related to negative emotional reactions to visualizations displaying their academic performance. RQ3 will address this hypothesis.

Research Questions

RQ1) Does revising the AGT instrument: Patterns of Adaptive Learning (Midgley et al., 2000), with language that focuses on information representation yield stable and reliable factors?

RQ2) Is there empirical support for scales that measure general motivational orientations towards information representation in a manner that is parallel to, but distinct from, the PALS scale?

The following research questions investigate the possible relationship between the proposed constructs, students' affective responses to various representations, and students' attributions once they are shown a graph that depicts them failing or succeeding in a given course. The following research questions are exploratory, without a priori assumptions or hypotheses for how the proposed constructs will relate to students' attributions toward their academic performance in a course.

RQ3) Assuming a stable and reliable factor structure is found, are any of the proposed constructs predictive of:

a. Students' stated emotional reactions to specific graphical representations (e.g., doing worse than the class average).
b. Students' attributions (e.g., stable, internal, and controllable) for their performance after seeing specific graphical representations.
c. Students' selections of specific areas of representations that are salient, or otherwise important features (e.g., selecting the end of a downward trending line in a line graph).
d. Academic outcomes of interest (e.g., GPA).

Method

Two analytic steps were taken to address RQ1-RQ3. First, confirmatory factor analysis (CFA) was used to validate the proposed instrument internally (RQ1), and externally (RQ2). Factor analysis is used to reduce the number of measured dimensions associated with a given psychological construct. Specifically, "Factor analysis is often used to explain a larger set of j measured variables with a smaller set of k latent constructs," (Henson & Roberts, 2006). In the Patterns of Adaptive Learning (Midgley et al., 2000), which measures Achievement Goal orientations, there are a number of items (variables) that are designed to measure the three latent construct posited by the theory (mastery, performance-approach, and performance-avoid). Each item, while independent, is theorized to evoke responses that are driven by the construct the item measures. Thus, if a respondent has a strong mastery orientation, they will answer all mastery items similarly.

Confirmatory factor analysis (CFA) was used in this study to test the proposed *a priori* factor structure. As a hypothesis testing technique, CFA requires items to load onto pre-identified factors (Harrington, 2008; B. Thompson, 2004). This allows the confirmation (or rejection) of the hypothesized factor structure. The hypothesized model (Figure 29) estimates 62 parameters implementing the maximum-likelihood (ml) method with 344 degrees of freedom (df). A sample size of n = 551 is more than sufficient for .80 power using MacCallum's (1996) power calculation tables.

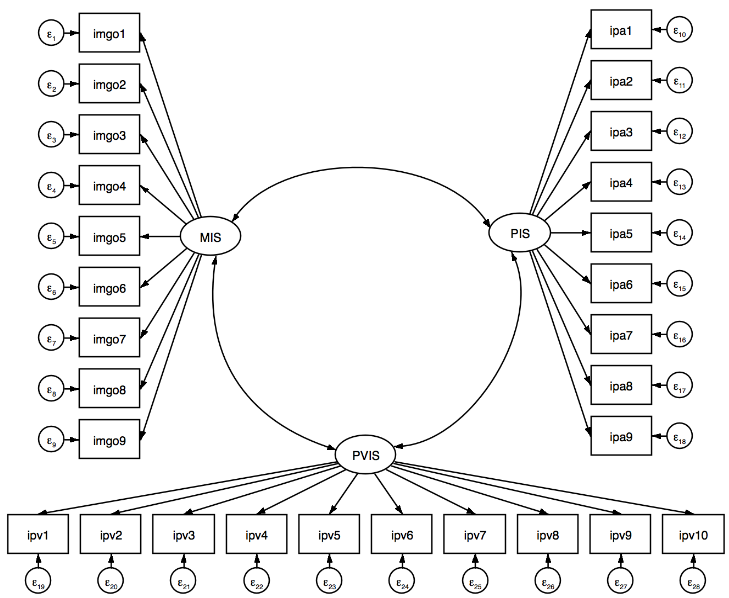


Figure 29. Hypothesized factor structure of students' information-seeking motivational orientations

Goodness of fit indices included the comparative fit index (CFI), root mean standard error of approximation (RMSEA), and standardized room mean squared of the residual (SRMR). Targeted fit values will be CFI > .95, RMSEA <.05, and CFI <.08. The hypothesized model was tested first; subsequent changes to the hypothesized model were based on prevailing theory with limited use of data-driven modification indices. Once stable factors were internally validated, CFA was also used to test whether or not the MISQ does in fact measure unique constructs when compared to PALS motivational constructs (RQ2). The proposed model was determined by first ruling out various alternative models that combined both proposed and established factor structures (e.g., Lauermann & Karabenick, 2013).

Regression analysis was used to test the relationship between the MISQ constructs and non-cognitive outcomes of interest, after controlling for demographic characteristics, academic variables, and AGT motivation measures. The following regression equation was specified:

$$Y_i = \beta_0 + \beta_1 FEMALE + \beta_2 PELL + \beta_3 FIRSTGEN + \beta_4 MINORITY + \beta_5 HSGPA + \beta_6 TERMGPA + \beta_7 CUMGPA$$
$$+ \beta_8 MIS + \beta_9 PAIS + \beta_{10} PVIS + \beta_{11} PAPPROACH + \beta_{12} PAVOID + \beta_{13} MASTERY$$
$$+ \beta_{14} SELFEFFICACY + \varepsilon$$

Dependent variables (Y_i) included the following: the predictive power of as they relate to emotional responses to representations (RQ3a), and attributions for course performance (RQ3b). A total of three regressions were specified per research question, for a total of 6 regression equations. Three regression equations to test the relationship between MISQ constructs and academic outcomes (Y_{GPA}; high school GPA, term GPA, and cumulative GPA), after controlling for relevant variables (RQ3d) were specified as follows:

$$Y_{GPA} = \beta_0 + \beta_1 FEMALE + \beta_2 PELL + \beta_3 FIRSTGEN + \beta_4 MINORITY + \beta_5 GPA1 + \beta_6 GPA2 + \beta_8 MIS + \beta_9 PAIS$$
$$+ \beta_{10} PVIS + \beta_{11} PAPPROACH + \beta_{12} PAVOID + \beta_{13} MASTERY + \beta_{14} SELFEFFICACY + \varepsilon$$

While the online survey enabled participants to select portions of the graph they found important, after data collection was complete it was discovered that a limitation of this process made impossible to disaggregate students' selection of salient features (RQ3c). Thus, it was not possible to test for the relationship between MISQ constructs and what graph features respondents selected as important. In lieu of this, aggregate results of those selections are presented instead.

Sample

Participants were recruited via Qualtrics Panels (a service of Qualtrics Surveys). The service facilitated the detection of unusable data, such as "straight-lining," where participants answer the same answer for all questions. Pilot testing was also conducted to remove data from "speed takers," i.e., participants that finished the survey as quickly as possible, likely without reading the questions. This ensured that all data collected was usable for analysis.

In order to participate in this study, participants were required to be currently enrolled in a post-secondary institution and be under 25 years old. Participants were also balanced on gender, and Pell grant recipient status (a proxy for lower socio-economic status). Participation was voluntary, and participants were given a $5 honorarium to complete the survey.

The final sample ($n = 551$), was drawn from college students from around the country, but is not intended to be representative of college students. Participants ages ranged from 18-25 ($M = 2.79$, $SD = 2.07$). Participants were racially and ethnically diverse. Full descriptive statistics of demographic information is shown in Table 5.

Table 5. Categorical Variable Descriptives

	N	*Percentage*
Female	294	53.94
Race/Ethnicity		
White	371	67.33
Hispanic/Latino	65	11.80
Black/African-American	45	8.17
Native American/American-Indian	6	1.09
Asian/Pacific Islander	3	9.62
Other	11	2.00
Year in School		
Freshman	169	3.67
Sophomore	116	21.05
Junior	124	22.50
Senior	118	21.42
Other	24	4.36
College		
Pell Recipient	275	49.90
First Generation College Student	202	36.66

Notes. Total respondents n = 551.

Procedure

Before the survey was sent to participants, cognitive interviews were conducted to ensure validity of the initial MISQ item pool. Cognitive interviews serve as a qualitative method to test for internal validity; participants of cognitive interviews are asked to interpret survey questions, ensuring that items are interpreted in a manner that is consistent with their designed intent (Karabenick et al., 2007). Participants for cognitive interviews were recruited from the psychology student subject pool at the University of Michigan. Cognitive interviews were conducted in two waves. Initial items were piloted by asking participants (n = 25) to read pilot items out loud, and then interpret their meaning. Items were revised according to misunderstandings, and then re-tested via another round of interviews (n = 10). The revised

MISQ consists of 28 items which tested well in the final round of cognitive interviews (see Appendix E for all items).

Survey. The survey taken by participants was divided into four sections. The first collected demographic information used to screen participants and ensure the final sample was balanced on gender and Pell grant status. The second section contained the proposed MISQ instrument, with a total of 28 items measuring three constructs (RQ1). The third section randomly split respondents into three groups, each taking a nearly identical survey, with the exception of the particular representation shown to them (described below). At the beginning of this section students were asked to choose "an important course that [they planned] to take in the future." Their responses were carried forward, and used to contextualize the representation they were shown in section three of the survey (See Appendix D for full survey instrument).

Section three also contained self-efficacy items drawn from the Motivation Strategies for Learning Questionnaire (MSLQ) (Pintrich, 2004), as well as items designed to capture their affect towards a representation (RQ3a), their attributions towards their hypothetical performance represented (RQ3b), and depicted information they deemed important (RQ3c). The final section was the Patterns of Adaptive Learning Scale (PALS, Midgley et al., 2000), which was used to test whether the proposed constructs within the MISQ instrument were distinct from AGT constructs as measured by PALS (RQ2).

Representations. Line graphs were used to represent progress in a hypothetical course of a students' choosing. Each graph showed comparative information, i.e., students' progress was cast against the class average. Graph 1b (below) consisted of an individual performance line and a line depicting the class average. This graph was designed to afford comparative information, and is consistent with either performance-avoid or performance-approach orientations (Figure 30).

Upward trending graph. Graph 1b represented 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 was always be 5% points higher (i.e., if the individual line showed 73% by week 14, then the class average lien showed 78%).

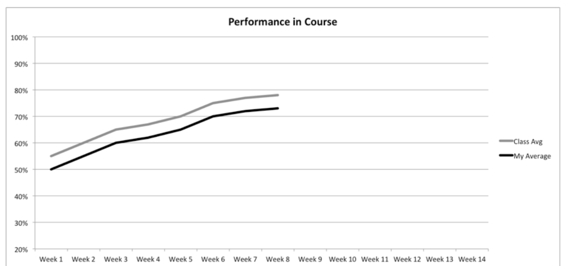


Figure 30. Graph 1b, comparative

Downward trending graphs. Graph 2b, and graph 2c were designed to have performance affordances, and included a class average line. Graph 2b depicted respondents' performance as well as the average performance of the class (Figure 31). The class average line was also perfectly parallel to a students' performance line, but positioned to always be 5% points higher. The second 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 six of the term.

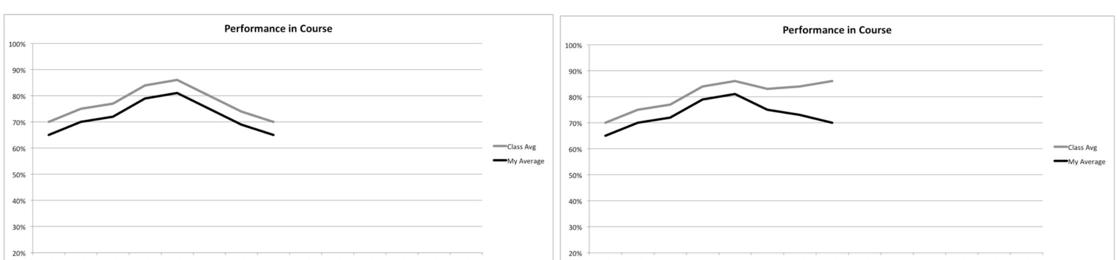


Figure 31. Graph 2b (left), and Graph 2c (right)

Measures

Measures were taken from the Patterns of Adaptive Learning Scale (Midgley et al., 2000), the Motivated Strategies for Learning Questionnaire (Pintrich & de Groot, 1990a), and were also written for this study. Items grounded in attribution theory (RQ3b), and items measuring students' affective responses to graphs (RQ3a) were written for this study, and not drawn from the literature. Academic outcomes (RQ3d) were measure via self-report, as there was no other way to reliably obtain this information. Salience was measured via a Qualtrics survey feature where students clicked on the area of a graph students' decided was most salient to them.

Information-seeking. The proposed Motivated Information-seeking Questionnaire (MISQ) is a survey instrument which consists of 28 items that measure students' affinity towards information that is either self-focused, or comparative. These two dimensions parallel mastery, performance-approach and performance-avoid dimensions as described by AGT and measured by PALS. All items are measured on a 5-point Likert scale with "not at all true of me" and "very true of me" serving as anchors. Table 6 provides sample items, as well as descriptive statistics for the items.

Table 6. Advising actions predicting changes in Motivation

Survey Items	ID	Mean	SD	Min	Max
Mastery Information-seeking Orientation					
It's important for me to only see information that shows my progress in class.	imgo1	3.33	1.20	1.00	5.00
I strongly prefer to see information that proves that I have learned a lot of new skills in class.	imgo2	4.06	.96	1.00	5.00
It's important for me to see information that shows that I have I improved my skills in class.	imgo3	4.12	.99	1.00	5.00
Performance-Approach Information-seeking Orientation					
It's important for me to see information that shows me doing better than other students in class.	ipa1	2.98	1.18	1.00	5.00
It's important for me to see information that shows that I am smart compared to others in class.	ipa2	2.99	1.22	1.00	5.00
I strongly prefer to see information that shows me being ahead of other students in class.	ipa3	3.23	1.25	1.00	5.00
Performance-Avoid Information-seeking Orientation					
I don't want to see information that makes me look stupid.	ipv1	3.30	1.31	1.00	5.00
It's important for me to not see information that shows me knowing less than others in class.	ipv2	2.85	1.22	1.00	5.00
One of my goals in class is to avoid seeing information that implies that I have trouble doing the work.	ipv3	2.83	1.23	1.00	5.00

Academic achievement. Academic achievement is measured through respondents' self-report of their high school grade point average (GPA), the GPA of their current term in college, and their cumulative GPA.

Motivation. The Patterns of Adaptive Learning Scale (Midgley et al., 2000) was administered to all participants at the end of the survey. The PALS scale measures students' achievement goal orientations as conceptualized by AGT (see Appendix C for full PALS instrument). The self-efficacy section of the Motivation Strategies for Learning Questionnaire (MSLQ) was also used (Pintrich, 2004). All items were measured on a 5-point Likert scale with "not at all true of me" and "very true of me" serving as anchors. Students took this section proceeding their view of the each of the representations. See Table 7, below, for descriptive statistics.

Table 7. Continuous Variable Descriptives

	N	M	SD	Min	Max	Alpha
Demographic						
Age	551	2.80	2.1	18	25	--
Academic						
High School Grade Point Average	485	3.64	.63	.00	5.00	--
Last Term's Grade Point Average	453	3.44	.65	.00	5.00	--
Cumulative College Grade Point Average	426	3.46	.59	.00	5.00	--
Motivation (PALS)						
Mastery	551	4.37	.73	1	5	.92
Performance-Approach	551	3.01	1.07	1	5	.91
Performance-Avoid	551	3.35	.99	1	5	.83
Self-Efficacy (MSLQ)						
Graph 1b participants	201	3.99	.76	1	5	.92
Graph 2b participants	186	3.88	.79	1	5	.92
Graph 2c participants	164	3.92	.72	1	5	.92

Notes. Total respondents n = 551.

Affect. Students' affective responses to one of three graphs were also measured via the question: "When I see my performance depicted in this way it…" with answers ending with "makes me feel" angry/sad/etc. All items were measured on a 5-point Likert scale with "not at all true of me" and "very true of me" serving as anchors. Table 8 presents summary statistics for each affective response measured, organized by graph type.

Table 8. Continuous Variable Descriptives

Descriptives

	N	M	SD	Min	Max
Graph 1b Affect					
…makes me feel angry	201	2.96	1.22	1	5
…makes me feel sad	201	3.50	1.20	1	5
…makes me feel happy	201	2.10	.99	1	5
…upsets me	201	3.70	1.02	1	5
…makes me feel curious	201	3.32	1.16	1	5
…makes me feel proud	201	1.70	.92	1	5
…makes me feel anxious	201	4.12	1.05	1	5
…makes me feel content	201	1.98	1.15	1	5
Graph 2b Affect					
…makes me feel angry	186	3.45	1.22	1	5
…makes me feel sad	186	3.83	1.19	1	5
…makes me feel happy	186	1.75	.99	1	5
…upsets me	186	4.15	1.02	1	5
…makes me feel curious	186	3.32	1.16	1	5
…makes me feel proud	186	1.70	.92	1	5
…makes me feel anxious	186	4.12	1.04	1	5
…makes me feel content	186	1.98	1.14	1	5
Graph 2c Affect					
…makes me feel angry	164	3.47	1.22	1	5
…makes me feel sad	164	3.98	1.14	1	5
…makes me feel happy	164	1.49	.81	1	5
…upsets me	164	4.12	1.22	1	5
…makes me feel curious	164	3.41	1.27	1	5
…makes me feel proud	164	1.5	.92	1	5
…makes me feel anxious	164	4.16	1.15	1	5
…makes me feel content	164	1.73	1.03	1	5

Notes. Total respondents n = 551.

Attributions. To measure to what causes students' attributed their performance, they were prompted with the following: "Below are some possible causes for why you are consistently below the class average:"

- I'm not very good at this sort of course (Internal)
- The professor was a difficult grader (External)
- I always have bad luck with these types of courses (Stable)
- This has been an unusually difficult term for me (Unstable)
- I could have studied more, but I didn't (Controllable)

Respondents were then asked to indicate how true each of the possible dimensions were for them. All items were measured on a 5-point Likert scale with “not at all true of me” and “very true of me” serving as anchors. See Table 9 for summary statistics on each attributional response measured, organized by graph type.

Table 9. Continuous Variable Descriptives

	N	M	SD	Min	Max
Graph 1b Attributions					
Internal	201	2.47	1.20	1	5
External	201	3.18	1.17	1	5
Stable	201	2.22	1.04	1	5
Unstable	201	3.45	1.12	1	5
Controllable	201	3.73	1.18	1	5
Graph 2b Attributions					
Internal	186	2.75	1.34	1	5
External	186	3.23	1.16	1	5
Stable	186	2.54	1.22	1	5
Unstable	186	3.52	1.06	1	5
Controllable	186	3.86	1.11	1	5
Graph 2c Attributions					
Internal	164	2.47	1.22	1	5
External	164	3.23	1.10	1	5
Stable	164	2.17	1.10	1	5
Unstable	164	3.55	1.13	1	5
Controllable	164	3.81	1.14	1	5

Notes. Total respondents n = 551.

Results

Hypothetical Courses Chosen

Students were asked to choose an important course that they planned to take in the future. Roughly one third of respondents (36%) chose a STEM course (defined as any science, technology, engineering, or math course), while another third (29%) chose a professional course (defined as any course focused on workforce development, such as teaching, business, etc.). 11% of students did not specify a particular course. Their responses are summarized in Figure 32, below.

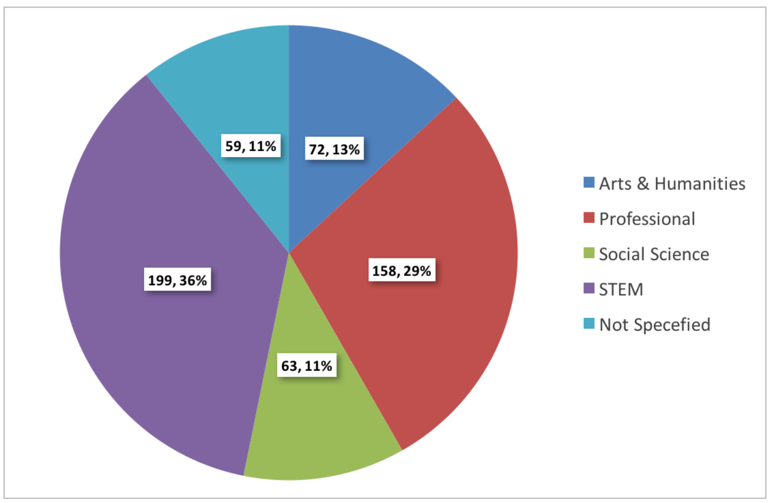


Figure 32. Hypothesized Factor Structure of Students' Information-seeking Motivational Orientations

RQ1: Internal Validity Confirmatory Factor Model

Hypothesized model. The hypothesized model was run in Stata 13 using the maximum likelihood estimation (ml, no missing values) method (n = 551). Statistically significant standardized coefficients ($p < .001$) are shown in Figure 33 below. The correlation between mastery information-seeking (MIS) and performance-approach information-seeking (PAIS) was not statistically significant. Most factors have high to moderately to high loadings on items (imgo2 and imgo3 have lower loadings). Goodness of fit statistics indicated an ill-fitting model ($\chi^2(348) = 1203.6$, $p < .001$; CFI = .86; RMSEA = .06; SRMR = .80).

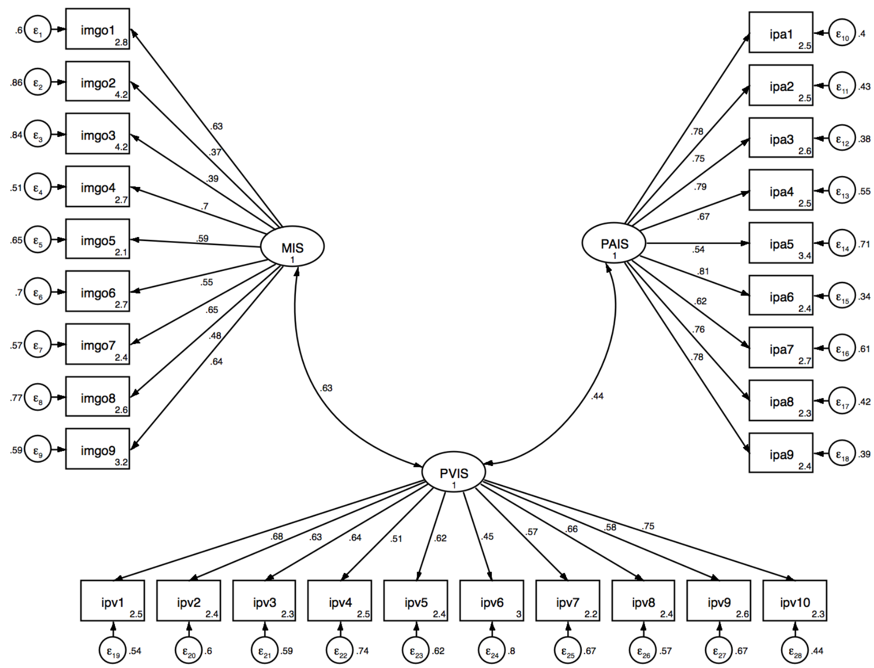


Figure 33. Test of hypothesized MISQ three factor structure, CFI = .86; RMSEA = .06; SRMR =.80

Four factor model revision. Since the hypothesized model was ill fitting, it was revised. Given MIS's usually high relationship to PVIS (.63), and its lack of relationship to PAIS, it was hypothesized that mastery items had avoid content. Individual items were also examined and it was determined that some mastery items had avoid language, e.g., mastery item 8: "I don't like information that compares my academic performance to anyone else."

This suggested a possible bifurcation of MIS into approach and avoid dimensions. To test this hypothesis, individual MIS items were correlated with a scale of PVIS items. MIS items that moderately to highly correlated with PVIS (p >.3) were used to test as a mastery-avoid construct.

This resulted in a 2x2 model, with mastery-avoid, mastery-approach, performance-avoid, and performance-approach serving as constructs. The revised model was run in Stata 13 using the maximum likelihood estimation (ml, no missing values) method (n = 551). Statistically significant standardized coefficients ($p < .001$) are shown in Figure 34 below.

Goodness of fit statistics indicated a somewhat ill-fitting model ($\chi^2(344) = 1065.7$, $p < .001$; CFI = .89; RMSEA = .06; SRMR = .74. Using model estimates from the hypothesized three-factor model, and the revised four-factor model, a likelihood-ratio test was conducted to determine if the revised model was, despite being ill-fitting, still a better-fitting model than the hypothesized model. Results indicated that the revised model (shown in Figure 34) was a better fit when compared to the hypothesized model ($\chi^2(4) = 137.88$, $p < .001$.)

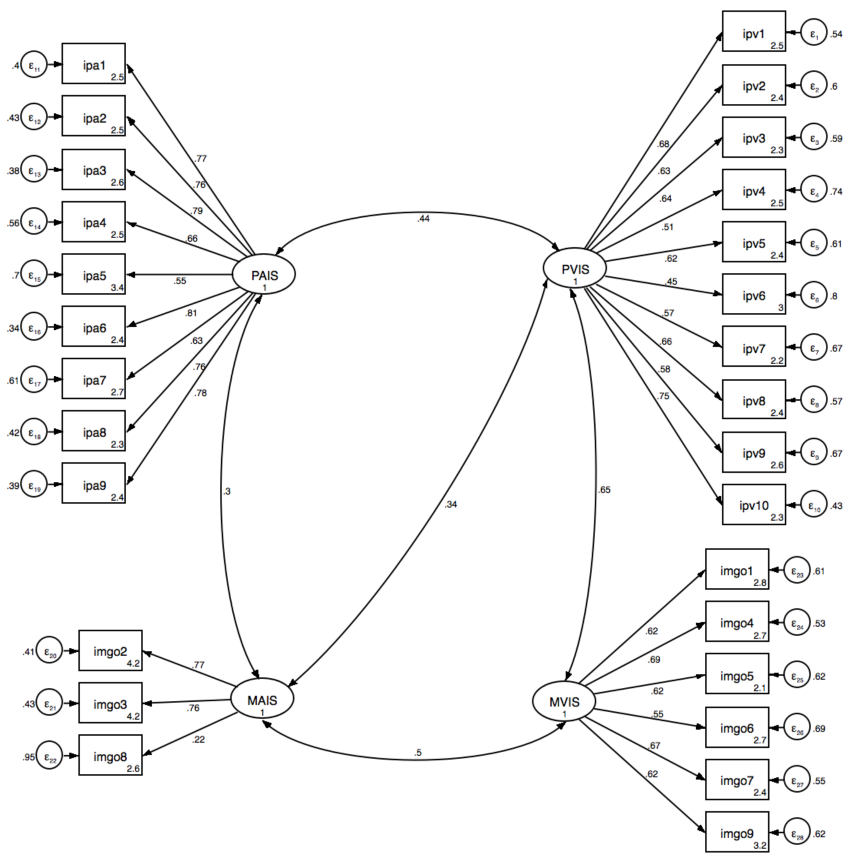


Figure 34. Test of revised four factor structure of MISQ; $\chi^2(344) = 1065.7$, $p < .001$; CFI = .89; RMSEA = .06; SRMR = .74

Two factor performance approach/avoid model. Given the poor fit of both the hypothesized model and the revised model which attempted to split mastery into mastery-approach information-seeking and mastery-avoid information-seeking, a CFA was conducted without including mastery items to determine if the hypothesized performance-oriented constructs (performance-approach information-seeking and performance-avoid information-seeking) would yield two stable factors. Goodness of fit statistics indicated a well-fitting model: $\chi^2(151) = 37.78$, $p < .001$; CFI = .95; RMSEA = .051; SRMR = .05, supporting a performance-approach information-seeking (PAIS) and performance-avoid information-seeking (PVIS) two-factor structure (Figure 35).

This two-factor structure was compared to an omnibus one-factor model, where all performance items loaded onto a single performance latent variable. Goodness of fit statistics indicated a poor fit: CFI = .705; RMSEA = .124; SRMR = .124, further lending evidence for a two factor solution.

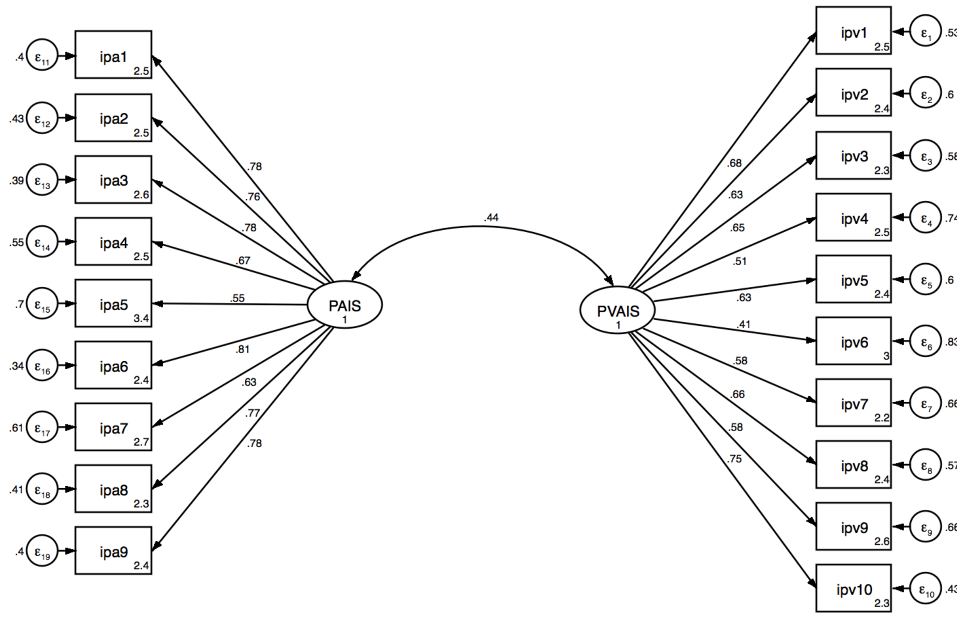


Figure 35. Test of revised four factor structure of MISQ; $\chi^2(151) = 37.78$, $p < .001$; CFI = .950; RMSEA = .051; SRMR = .053

(Re)Incorporating mastery items. Given the acceptable fit of a two factor PAIS and PVIS solution, scales of PVIS and PAIS items were created (α = .85 and .91, respectively). Due to the high correlation between the MIS and PVIS latent variables in the tested hypothesized model (r = .63, Figure 34 above), the new PVIS scale was correlated with individual MIS mastery items to determine which MIS items cold be omitted in order to include a revised version of Mastery Information-Seeking (MIS). Unsurprisingly, all MIS items were correlated with the PVIS scale (Table 10). All items that correlated with the PVIS moderately or highly (p >.3) were eliminated. Thus, only items 2, 3 and 8 were retained.

Table 10. Mastery information-seeking correlations with PVIS

	ID	Corr.
It's important for me to only see information that shows my progress in class.	imgo1	.35
I strongly prefer to see information that proves that I have learned a lot of new skills in class.	imgo2	.22
It's important for me to see information that shows that I have I improved my skills in class.	imgo3	.29
Information shown to me about my class should only be about how I am doing, not how others are doing.	imgo4	.38
Seeing information about how other students are doing in class interferes with my learning.	imgo5	.49
Only seeing information about how I am doing in class helps me learn better.	imgo6	.33
I don't like information that compares my academic performance to anyone else.	imgo7	.45
I don't need to see information about other student's progress in class because it doesn't really matter.	imgo8	.19
Information that only shows my own progress helps me focus on improving myself.	imgo9	.30

A CFA was conducted including the three mastery items to determine if the modified three-factor model would yield three stable factors. Goodness of fit statistics indicated a marginal fit: χ^2 (247) = 242.1, $p < .001$; CFI = .91; RMSEA = .06; SRMR = .08 shown in Figure 36. While it is possible that there are mastery dimensions of motivated information-seeking, the items written to detect such a construct proved to be inadequate. Consequently, the two-factor model including the performance-approach information-seeking (PAIS, $\alpha = .85$), and performance-avoid information-seeking (PVIS, $\alpha = .91$) was used to answer RQ2 and RQ3. These two scales were thus retained for external validity testing (below).

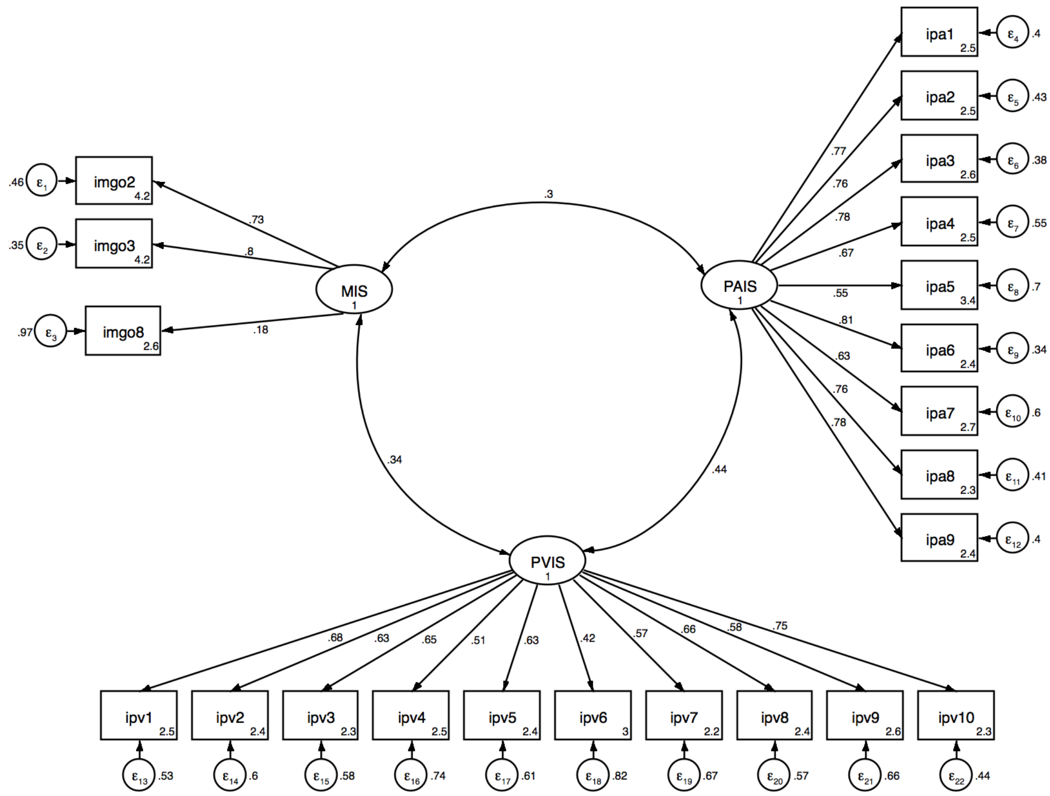


Figure 36. Test of revised three factor structure of MISQ; χ^2(247) = 242.1, *p* < .001; CFI = .91; RMSEA = .06; SRMR = .08

RQ2: External Validity of Two-Factor PAIS and PVIS Confirmatory Factor Model

External validity, comparison to PALS. In order to test whether the PAIS and PVIS constructs were empirically distinguishable from the standard AGT performance constructs, two CFAs were conducted. The first was a four factor solution, consisting of: AGT performance-approach (PA), AGT performance avoid (PV), and their information-seeking counterparts (PAIS and PVIS). The second was a two factor solution which aggregated PAIS items with PA, and PVIS items with PV.

Four factor solution. A four factor solution yielded a model with an acceptable fit (Figure 37): χ^2(344) = 863.3, p < .001; CFI = .936; RMSEA = .052; SRMR = .049 (Figure 37).

This lends support that the constructs of performance-approach and performance-avoid, as measured by PALS (Midgley et al., 2000), are empirically distinguishable from the proposed constructs of performance-avoid information-seeking, and performance-approach information-seeking.

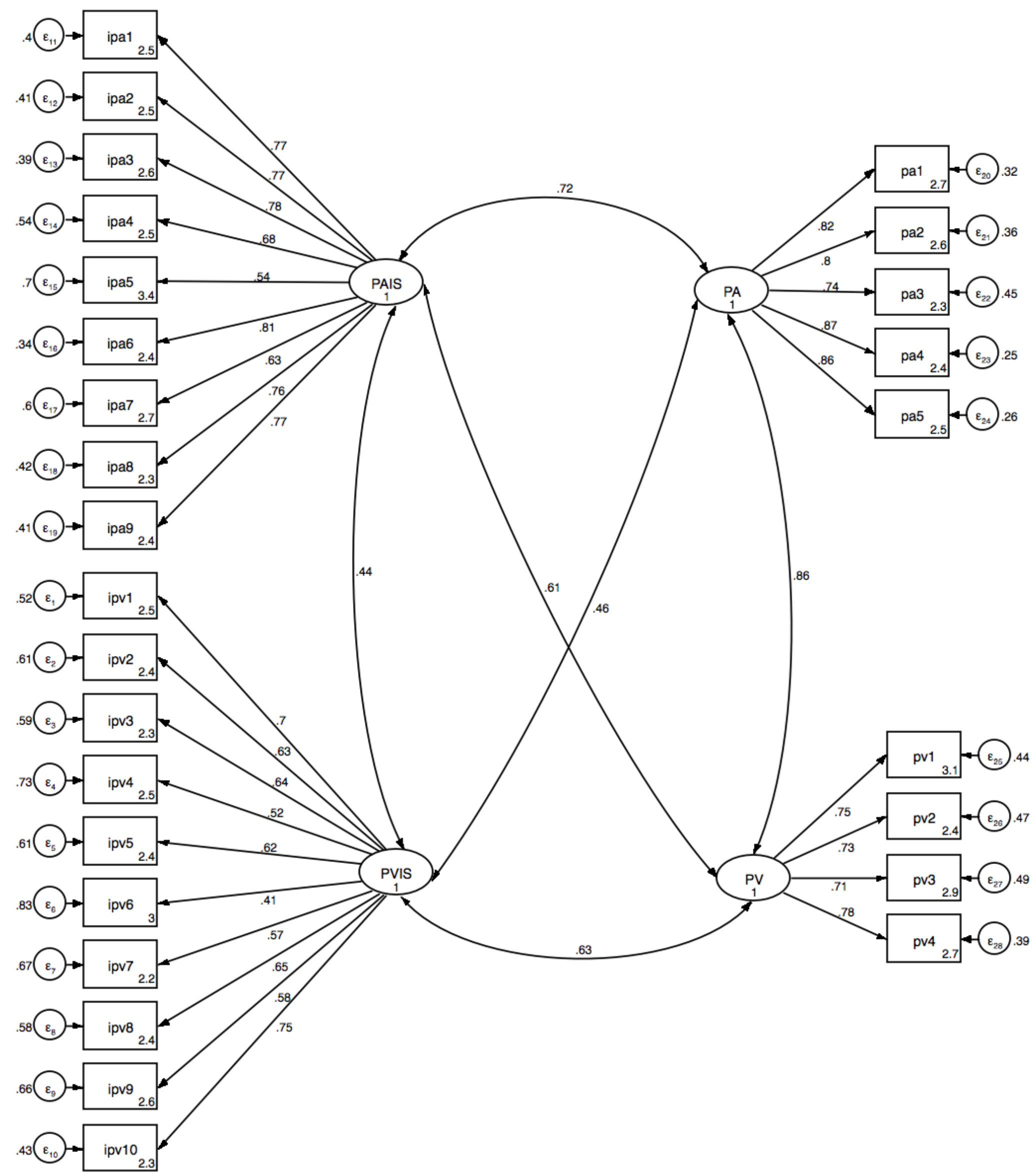


Figure 37. Test of four factor structure distinguishing PALS from MISQ; $\chi^2(344) = 863.3$, $p < .001$; CFI = .936; RMSEA = .052; SRMR = .049

Two factor solution. A two factor solution yield a model with a poor fit: $\chi^2(349) = 2174.9$, p <.001; CFI = .774; RMSEA = .097; SRMR = .087 (Figure 38). This lends more support that the constructs of performance-approach and performance-avoid, as measured by PALS (Midgley et al., 2000), are empirically distinguishable from the proposed constructs of performance-avoid information-seeking, and performance-approach information-seeking.

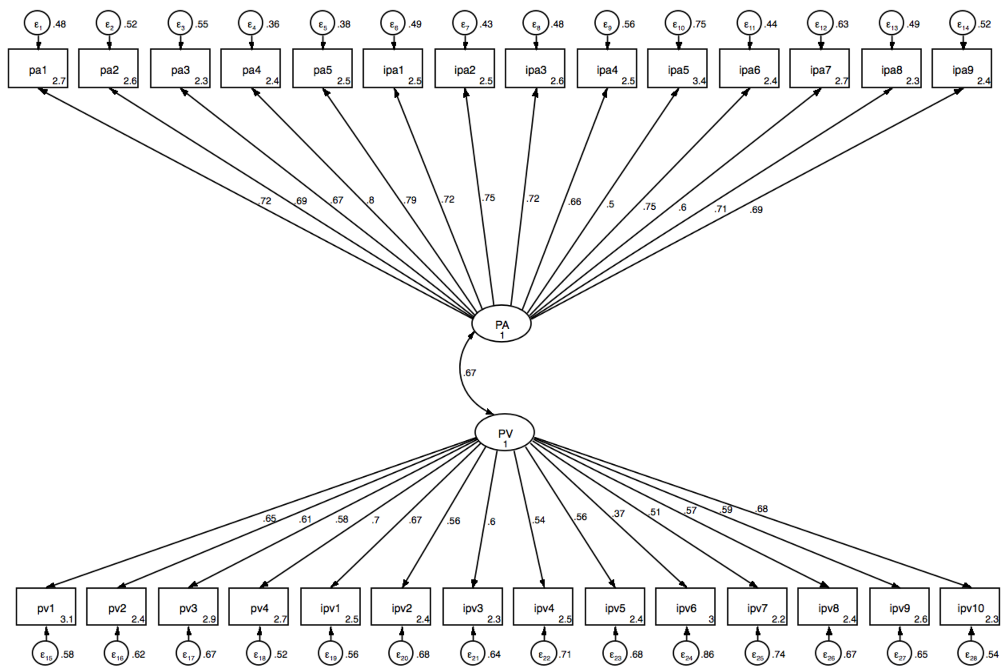


Figure 38. Test of two factor structure combining PALS from MISQ; $\chi^2(349) = 2174.9$, *p* <.001; CFI = .774; RMSEA = .097; SRMR = .087

RQ3: Predictive Power of MISQ Constructs

CFA analysis yield two stable factors (performance-avoid/approach information-seeking) that are empirically distinguishable from their AGT counterparts. RQ3a-d were posed to test the predictive power of these new constructs as they relate to emotional responses to representations (RQ3a), attributions for course performance (RQ3b), and academic outcomes (RQ3d). It was not possible to disaggregate students' selection of salient features (RQ3c). Aggregate results of those selections are presented instead. Full regression tables can be found in Appendix E, the results below present information intended to summarize the outcomes of interest MISQ constructs predict; controls that are predictive are also discussed. An MIS variable was not used in regression equations due to the fact that the construct was not validated.

Emotional reactions (RQ3a). After controlling for relevant demographic characteristics, academic achievement, and other motivational variables, regression analysis indicated that students' PVIS and PAIS scores were significantly negatively related to only one positive emotion: curiosity. PVIS was negatively related to curiosity for students who saw the upward trending graph, and PAIS was negatively related to students who saw the divergent graph (Table 11).

Table 11. PVIS and PAIS Measures Predicting Positive and Negative Affect, Controlling for Demographic, Academic, and other Motivational Variables

	Graph Type					
	Upward Trending		Downward Trending		Divergent	
	+	-	+	-	+	-
Positive Affective Response						
Proud						
Curious		PVIS				PAIS
Happy						
Content						
Negative Affective Response						
Upset						
Angry	PVIS		PVIS		PAIS	
Sad			PVIS		PVIS	
Anxious					PAIS	

Notes: Only significant MISQ predictors shown. See Appendix F for full regression results

Both constructs were also significantly related to nearly every negative emotion, including anger, sadness, and anxiety. For upward trending graphs, PVIS was positively related to anger. For downward trending graphs, PVIS was positively related to both anger and sadness. For divergent graphs PVIS was positively related to sadness, while PAIS was positively related to anger and anxiety. Overall this pattern indicates that students who seek information in a performance-avoidant (PVIS) manner also report feeling stronger negative emotions, while sometimes feeling less curiosity—though a causal claim cannot be made.

Attributions (RQ3b). After controlling for relevant demographic characteristics, academic achievement, and other motivational variables, regression analysis indicated that PVIS was significantly, and positively, predictive of students attributing their performance to external, stable, and unstable factors for downward trending graphs. These attributions roughly track with excuse making; the item for external attributions blamed the professor for poor performance, stable attributions were a result of always having "bad luck," and unstable attributions were a result of an "unusually" difficult term.

After controlling for relevant demographic characteristics, academic achievement, and other motivational variables, regression analysis indicated that PAIS significantly, and positively, predictive of students attributing their performance to internal ("I'm not very good at this sort of course"), stable ("I always have bad luck with these types of courses"), and controllable ("I could have studied more, but I didn't") factors (Table 12). These attributions are more inward looking, and tend to place responsibility on the student for poor performance. Neither PAIS or PVIS was predictive of any attributions to the divergent graph.

Table 12. PVIS and PAIS Measures Predicting Attributions, Controlling for Demographic, Academic, and other Motivational Variables

	Graph Type					
	Upward Trending		Downward Trending		Divergent	
	+	-	+	-	+	-
Attributions						
Internal	PAIS					
External			PVIS			
Stable	PAIS		PVIS			
Unstable			PVIS			
Controllable	PAIS					

Notes: Only significant MISQ predictors shown. See Appendix E for full regression results

Academic outcomes (RQ3d). Neither PAIS or PVIS was predictive of any academic outcome, after controlling for previous academic achievement and relevant demographic characteristics. Pell status was negatively associated with high school GPA, and mastery was negatively associated with cumulative GPA ($p < .05$) after controlling for demographic characteristics and previous academic achievement (Table 13).

Table 13. Motivation Measures Predicting GPA Controlling for Demographic Variables

	Academic Outcomes (DV)					
	High School GPA		Term GPA		Cumulative GPS	
Demographic						
Female	-.02	.06	.01	.04	.01	.04
Pell	-.15**	.06	-.01	.04	.02	.04
First Generation	-.05	.06	-.04	.04	.06*	.04
Minority	.05	.03	-.01	.02	-.04	.02
Academic						
HS GPA	--	--	.02	.03	.15***	.03
Term GPA	.04	.08	--	--	.74***	.03
Cum. GPA	.36***	.08	.78***	.04	--	--
Motivation						
PA Info Seeking	-.01	.04	.04	.03	.01	.03
PV Info Seeking	.05	.04	-.05	.03	.03	.03
Performance-Approach	-.01	.05	.00	.03	.04	.03
Performance-Avoid	-.03	.05	.00	.03	-.04	.03
Mastery	.08	.04	.06	.03	-.07*	.03
Self-Efficacy	.04	.04	.02	.03	.06	.03
R^2	.20		.65		.67	

Notes. . *p < .05 **p < .01 ***p < .001. Variables entered into the model simultaneously. Each column represents a different regression model and standard error, respectively.

Salience of information (RQ3c). Salience was measured by having students select the area of the graph they felt communicated the most important information. Figure 39, below, illustrates click patterns across each three groups of students, with red indicating more clicks, and light blue indicating less.

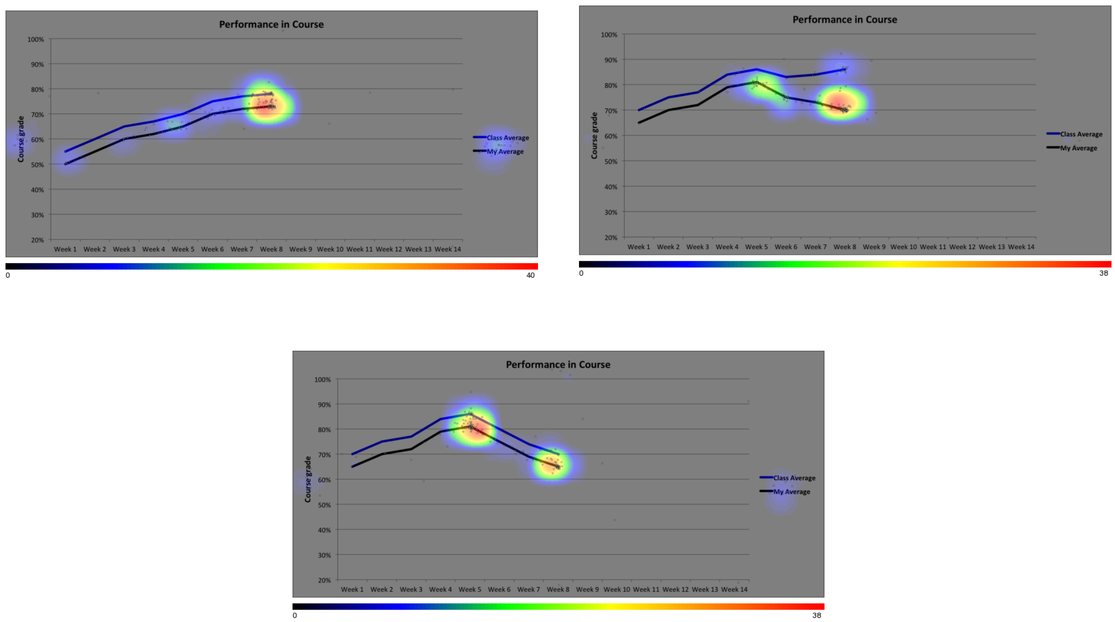


Figure 39. Graph 1b (left), Graph 2b (right), and Graph 2c (bottom)

For the upward trending graph (1a) students' selection of the most important area of the graph focused on their progress at the end of the term. The downward trending (2b) and divergent (2c) graphs had two main areas of importance; one where the graph began its downward trend, and again at the end of the term. These results indicate that most students believed the most recent academic information (i.e., the end of the line) was the most important. Students, however, also found the point at which their progress began its downward trend to be important.

Discussion

Hypothesis 1, which posited that information-seeking constructs that paralleled, but were distinct from, AGT constructs, was partially confirmed; performance-avoid information-seeking (PVIS), and performance-approach information-seeking (PAIS) were shown to be stable, and empirically distinguishable from their AGT counterparts. Mastery information-seeking (MIS), however, was not validated as a construct. This is likely due to avoidant language used in the items intended to measure mastery. The MIS item: "Only seeing information about how I am doing in class helps me learn better," for example, implies that there is other information that could be displayed, but should not be displayed. Many MIS items are worded in a similar manner, and cast what should be displayed against what should not. This "contrast" language may have proven to be a distraction from the main focus of the item, i.e., information that showed mastery. Further studies will have to be conducted to identity and measure mastery information seeking, if it can be measured at all; it is also possible that visualizations in academic settings are intertwined with performance in a manner that cannot be differentiated.

Hypothesis 2 was also partially confirmed. It was shown that PAIS and PVIS constructs were predictive of negative emotions, as well as students' attributions for their performance in a hypothetical course, even after controlling for AGT constructs, self-efficacy, and other academic and demographic variables. Participants who were shown upward trending comparative line graphs, for example, had PAIS scores that were positively related to internal, stable, and controllable attributions with regard to their performance in the hypothetical course. Students who were shown downward trending comparative graphs, on the other hand, had *PVIS* scores that were positively related to external, stable, and unstable attributions with regard to their performance in the hypothetical course. This suggests that there is an intertwined relationship between representations and participants' affinities toward certain representations. It could be that certain types of representations foreground affordances that evoke certain attitudes that are already present in leaners. (Recall that each participant took the MISQ before seeing *any* graph). Future work will have to disentangle this relationship.

Results suggest that the MISQ is a viable instrument that can be used to measure students' affinity towards visualizations. It should be noted, however, that the predictive power of the posited MISQ constructs varied by the type of visualization used (e.g., upward trending graph). This suggests that the graphs themselves have certain motivational information affordances. More work will have to be done to unpack how strong students' affinities are in comparison to the information communicated by a representation. Future work should examine visualizations that are generated using actual student achievement data in a digital environment students are familiar with. Doing so would have two advantages. First, the role that PAIS and PVIS play when students have a stake real information would be better understood any calculated effect sizes could be immediately contextualized (doing so in this study would not necessarily have been as meaningful.) Second, it would refine the role PVIS and PAIS play for various types of visualization; PVIS, for example may only be related to academic or non-cognitive outcomes when students are shown comparative graphs with small gaps between students' individual information and aggregate information. Once the gap grows large enough PVIS (or PAIS for that matter) may matter less. Understanding such boundaries would have theoretical and practical implications.

Regardless, the imperative to develop the MISQ instrument has pragmatic and theoretical dimensions. From a pragmatic standpoint such an instrument can potentially inform the design of graphic representations (e.g., graphs) that would be used in current and future student-facing learning analytics interventions. Designers could, for example, have students take a survey to measure their general motivational orientation towards graphic representations and ensure that students' personalized dashboards only contain graphic representations that were shown to be associated with adaptive outcomes. Conversely, such an instrument could also 'protect' students from representations that were shown to be associated with maladaptive outcomes.

From a theoretical standpoint, the development of this instrument suggests that there are underlying motivational constructs that drive how students "make-sense" of, or interpret, graphical representations of their achievement data. These constructs, are parallel to—and distinct from—those present in Achievement Goal Theory, i.e., mastery and performance avoid/approach orientations. Findings suggest that the emergence of the visualizations often used in digital learning environments may evoke interpretive stances toward the information represented in new ways that are not present in traditional brick and mortar learning environments. If this is the case, then it is important to better understand the motivational implications of such environments; the digital schoolhouse will only grow as products like Kahn Academy and MOOCs do. Successfully measuring PVIS and PAIS (or constructs like them), and relating them to outcomes of interest, suggests that educators as well as designers should be mindful of the perceived motivational affordances of a designed information environment (e.g., student-facing learning analytics intervention), as well as the classroom environment.

Chapter 5: Discussion

The efficacy of learning analytics applications is predicated on two intertwined processes. The first requires that valid techniques be used to uncover patterns about student learning and engagement—doing so defines what counts as "actionable" information (Arnold & Pistilli, 2012). The second requires actionable information to be communicated to stakeholders in a manner that prompts them to act in a way that is consistent with what the information affords. This generally occurs by distilling information into a set of representations (Pardo, 2014; Siemens, 2013). Understood in this way, the goal of any learning analytics application is to communicate actionable information effectively in hopes that various stakeholders make decisions that improve learning outcomes (e.g., retention, course outcomes, etc.). Since learning analytics applications utilize visualizations to represent actionable information, the ways that various stakeholders interpret those visualizations is critical and thus warrants study.

Despite this clear imperative to study visualizations themselves, the field of learning analytics has generally focused on developing quantitative techniques used to detect patterns in educational settings (Elbadrawy et al., 2015; see Harrison et al., 2015; Kennedy, Coffrin, de Barba, & Corrin, 2015; Miller et al., 2015 for examples). Consequently, there have few studies focused on potential errors, bias, user misunderstandings, and/or misinterpretation within either analytics or the representations they employ. This dissertation is a first step in filling this important gap in the literature. It investigates how students attend to the display of information related to their academic performance, and focuses on at-risk students because they represent a group that is likely to receive institutional support, which indicates they are more likely to be sent messages about their learning by an institution, or agents within that institution in order to facilitate their transition to college (Tinto, 1987; 1993; 1996).

The theories of Achievement Goal Theory (AGT), and Expectancy-Value Theory (EVT) framed the research, as well as their associated measures. Both Study 1 and Study 2 draw from each theory at various points, but are principally oriented around AGT which focuses on why students are motivated to accomplish their academic work, positing that they can be oriented toward performance (i.e., defining their success based on where they stand in comparison to others) or mastery (i.e., defining their success relative to their own growth) (Elliot & McGregor, 2001). Both studies lend support to the notation that performance and mastery can be made more or less relevant in visualizations based on whether or not they show information that is comparative (performance) or individualized (mastery).

In this chapter I summarize the findings of this dissertation and discuss how they contribute to both the learning analytics field and the field of student motivation. I also contextualize the findings by discussing their limitations, and suggest future avenues of research; in the end this dissertation represents the beginning of a potentially fruitful and exciting line of inquiry, rather than the end of one. The findings of this dissertation have implications for what we understand about student motivation in an information-rich environment, and informs how learning analytics applications might be designed with an eye toward encouraging adaptive forms of student motivation, or built to adapt to their motivational needs.

Summary of Major Findings

While there are many different sense-making processes and outcomes that are worthy of study in relation to visualizations of academic information, the present studies focused on visualizations' relationships to student motivation because academic success is predicated on students' motivation to succeed in educational contexts. Findings address a gap in the literature with respect to student motivation in relation to learning analytics by investigating how students interpret visualizations of their own academic performance. Study 1 (Chapter 3) captured students' sense-making in relation to five different graphic visualizations, and Study 2 (Chapter 4) measured these attitudes and validated two of the three constructs that the Motivated Information Seeking Questionnaire (MISQ) set out to measure. The MISQ subsequently measured students' motivated information-seeking orientations towards visualizations of their academic information.

Results from both studies suggest that students are not unbiased towards the information provided by learning analytics applications. Instead, their interpretations rely on how information is presented (Study 2), which can be shaped by the visualizations themselves (Study 1). Below I provide a summary of the major findings of each study.

Study 1: Capturing Sense-making of Visualizations

Study 1 was a qualitative investigation designed to capture a wide range of students' interpretive stances in relation to visualizations of academic achievement. Students interpreted five different iterations of a similar graph; two of which were designed as upward trending, and three of which were designed as downward trending (with the fifth graph showing a downward trending and divergent scenario).

Context. To contextualize the interview, students were asked to imagine that the graph depicted their own achievement in a course of their choosing. Students made diverse choices, ranging from STEM courses to language courses, thus representing a cross section of courses undergraduates likely take. Students' interpretations of every graph were well understood through the lens of AGT, with EVT interpretations centering on students' expectancies for success.

Differences among graphs. Self-focused graphs yielded predominately mastery related statements—if performance statements were found at all, they were non-valenced (i.e., neither approach or avoid oriented). Comparative graphs, on the other hand, elicited more performance, performance-avoid, and performance approach responses (in that order), although mastery statements were also expressed.

Most motivating graph. When students were asked to choose a graph that was "more motivating," they primarily chose a graph that was comparative. This was true for both the upward and downward trending graph. Students, moreover, found the divergent graph to be the most motivating when asked to choose among the downward trending graphs.

Predicting future performance. Aside from a couple of exceptions, students generally predicted growth across the five graphs shown, indicating that they felt they would improve. There were some differences in regards to the rate of their growth, however, and completed trend lines were often unrealistically optimistic (especially for the divergent scenario). Coded segments for graph prediction paralleled other findings; self-focused graphs elicited more mastery responses, while comparative graphs elicited more performance, performance-avoid, or performance-approach responses. (Performance-avoid codes were most common for comparative graphs, and were also coded for the self-focused downward trend line.)

Information evaluation. When students were asked to evaluate the information that was being communicated by each of the graph, the vast majority of them stated that they found the class average helpful (though there were a few vocal exceptions to this). When asked to comment on helpful graph features, students' responses ranged from finding the graph's design helpful, to the graph helping them think about study strategies. Students' also found the week-by-week organization of the graph helpful. Unhelpful features were generally not reported. When asked if the graphs could be improved by adding of other information, students reported that they would like to see more predictions of their progress, links to additional resources, or more granular grade information, such as breaking down their overall grade by exam and assignment scores.

Representation of self. Despite the results reported above, most students chose the upward trending self-focused graph as the best representation of themselves.

Study 2: Measuring Sense-making of Visualizations

Study 2 (Chapter 4) was a quantitative investigation focused on internally and externally validating the Motivated Information Seeking Questionnaire (MISQ). The MISQ is designed to measure three hypothesized constructs that are parallel to, but distinct from, the mastery, performance-approach, and performance-avoid constructs posited by Achievement-Goal theory (Elliot & McGregor, 2001; Midgley et al., 2000): mastery information seeking (MIS), performance-avoid information seeking (PVIS), and performance-approach information seeking (PAIS).

Once validated, the remainder of the study focused on whether or not any of the proposed constructs predictive students' emotional reactions to one of three graphs, attributions regarding their performance, and achievement information. Students were randomly split into three groups.

Each group saw either a comparative downward trending graph, a comparative upward trending graph, or a comparative divergent graph. The three graphs were the same as those in the Study 1.

Internal validation. Confirmatory Factor Analysis (CFA) partially confirmed the hypothesized factor structure, supporting a two-factor structure made up of the PVIS and PAIS factors. The MIS factor, however, was not supported by the data, which may have been due to the MIS items themselves, which require further refinement.

External validation. CFA was used to empirically distinguish PVIS and PAIS from their Achievement-Goal Theory counterparts (performance-approach and performance-avoid). Results of the CFA supported a four-factor structure over a two-factor model indicating that PVIS and PAIS were indeed empirically distinct from performance-approach and performance-avoid.

Predictive power. Regression analysis was used to assess the predictive power of PVIS and PAIS in relation to affective, attributional, and academic outcomes of interest. After controlling for relevant variables, analysis indicated that—depending on the graph shown—both constructs were negatively predictive of curiosity. PVIS was found to be positively predictive of anger for both upward and downward trending graphs, and was also positively predictive of sadness for the downed and divergent trending graphs. PAIS was positively predictive of anger for the divergent graph, as well as anxiety for the divergent graph.

Both constructs were also predictive of various attributions. PAIS was positively predictive of internal, stable, and controllable attributions after controlling for relevant variables for upward trending graphs. PVIS, on the other hand, was possibly predictive of external, stable, and unstable attributions for the downward trending graph. Neither construct predicted any outcome when students were shown the divergent trending graph. Neither construct predicted any academic outcome.

Salience. Limitations in data collection precluded the possibility of using PAIS or PVIS to predict what students found salient in each graph. Aggregate information, however, suggested that students found the end points of the graphs most salient, as well as the peaks of the downward trending graph.

Contributions

This dissertation contributes the understanding of students' academic motivation within an information environment by suggesting the importance of the new constructs introduced in Study 2. It also contributes to the field of learning analytics by highlighting the importance of visualizations, and their relationship to student motivation (Study 1 and 2). Findings from both studies also suggest potential design implications. Finally, this dissertation contributes to our understanding of how at-risk students might have certain interpretive inclinations when their academic information is represented via a visualization (Study 1). I will discuss each of these contributions in turn.

Motivation Theory

Tightly coupled with the idea of actionable information for students is the question: "Can I do this?" posed by Eccles and Wigfield (Eccles & Wigfield, 2002); with the associated question implicit in their theory: "Do I even want to do this?" The promise and perils associated with learning analytics applications revolve around these two questions. Visualizations of academic information serve as potential answers to the above questions. Yet, they do not simply answer the question but instead communicate more information that students can draw on to make subsequent decisions regarding how they might best approach a situation where they are struggling. Study 1 foregrounds the importance of visualizations of academic achievement and shows that graphs do not communicate information in a manner that is agnostic toward the information they contain; each graph has specific information affordances that interact with students' affinities towards certain types of information. Self-focused line graphs, for example, seem to afford mastery related sense-making by students, whereas comparative graphs afford performance related sense-making. This suggests that there is an interplay between the graphs themselves, and students' own affinities toward certain types of information. *Academic motivation in relation to visualizations, then, is shaped by both internal processes and the information environment to which students are exposed.*

This new information environment has not been examined in the academic motivation literature. Instead, work has focused on traditional learning environments, such as classrooms (e.g., Eccles & Harold, 2004; Harackiewicz et al., 1997; Perez et al., 2014). This dissertation expands potential contexts to the digital realm. Study 2, moreover, provides a tool (the MISQ) to undertake new studies that expand the applicability of Achievement-Goal Theory. It also suggests that how students interpret information is related to other motivational processes, such as their attributions for success or failure in a given context.

Learning Analytics

The present studies contribute to the learning analytics research field by providing tools that have the potential to inform the design of various applications intended to communicate the patterns in student learning that quantitative analyses uncover (see Arnold & Pistilli, 2012; Duval, 2011; Krumm et al., 2014; Verbert et al., 2013; Wise et al., 2013, for examples).

What distinguishes learning analytics applications from traditional modes of academic feedback (e.g., grades, or comments on an essay) is their capacity to extract data from user interactions with the learning environment, transform it through algorithms and computational processes, and "load" it onto applications designed to provide feedback that is personal, information rich, and quickly disseminated (Lonn et al., 2013). These applications, in theory, help stakeholders (e.g., students, administrators, academic advisors) identify trends both within and across different students, courses, and/or student populations by providing “actionable” information intended to support evidence-based decision making (Arnold & Pistilli, 2012).

On the one hand, learning analytics applications have the potential to give learners the tools to study themselves and hone their own study habits, making them “learning scientists,” of their own study practices. Doing so would make it more likely for students to answer ‘yes’ to Eccles’ and Wigfield’s hypothetical “can I” question. Given this, it is imperative for non-cognitive measures, such as student motivation, to be explored as potential sources of data for learning analytics applications in order to provide the most adaptive design. The MISQ provides one potential way that learning analytics applications can be adapted to the needs of each student. A learning analytics application could, for example, offer a shortened version of the MISQ via on onboarding processes. This would enable the application to personalize visualizations in a manner that would, at worst, prevent students from seeing visualizations shown to be related to maladaptive motivational orientations. At best, such adaption could be used to ensure that students were exposed to visualizations that would motivate them optimally. More work on the instrument will have to be conducted before it can be integrated into such a system. This includes collecting more data in authentic learning environments (discussed below).

Moreover, if we assume that the question, “Can I do this?” is ubiquitous among students, and learning analytics applications give students the resources to both understand and marshal resources to accomplish said task, then it is important to study the applications that frame and define the academic task being attempted. Study 1 explores this question qualitatively, and contributes to the understanding of particular visualizations known to be used by learning analytics applications (Krumm et al., 2014; e.g., Lonn et al., 2014). Thus, “Can I do this,” is a question that is intertwined with the information context made available to the student—one that is communicated by particular visualizations. Study 1 showed that the affordances of visualizations may in fact be predictable, or at least partially controllable.

Design Implications

Both Study 1 and Study 2 lend 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 harm;* and 3) *Always suggest a way for students to grow.* 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 dissertation suggest that students may not need more information to learn more. Indeed, more information may actually be maladaptive. Study 1 suggests that the more information is embedded in a visualization, the more variability there will be in how it is interpreted. (Students has 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 downside; 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 harm,” which refers to the idea that visualizations should not harm students’ ability to learn. “Harm,” is thus understood broadly, and subjectively. For example, 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 them to attribute failure to an uncontrollable source. They 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 them accountable. The MISQ is a step in the direction of measuring these attitudes and their associated consequences.

Regardless of the visualization used, maxim three (“*Always suggest a way for students to grow*”) serves as a check for designers. 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 students’ performance to that of his or her peers. An ethical learning analytics application, then, should supply this information, but also pair it with resources that students’ can bring to bear when they face challenges. Each student would, hypothetically, have their own personalized set of triggers for this information to be displayed. Conversely, the resources themselves could be personalized.

At-risk College Students

It should also be noted that learning analytics applications can be understood as the instantiation of the goals of various stakeholders, including the institutions that implement them.

Embedded in the design of a given application 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 applications automate this decision making process and extend the decision making powers of those who design them, as well as enable stakeholders to scale their decisions to thousands of students.

Study 1 explores how a specific student population (at-risk students) interpret visualizations of academic information. It suggests that at-risk students may have specific needs in this respect. Many were sensitive to comparative information, though they may also seek it. Comparative work will have to be done, however, to determine if there are any differences between at-risk students' interpretations of visualizations when compared to those of traditional college students. This tension between what information at-risk students are drawn to *versus* what information may be most appropriate is an important one. While neither study alleviates this tension, both provide a way in which it can be addressed in future research.

Limitations

While each study within this dissertation makes contributions to various literatures, neither is without its limitations. First, each study relies on the same set of representations: line graphs representing achievement over time in a manner that is either self-focused, or comparative. As noted in the methods section of each study, 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 each study in important ways.

Since both studies center entirely on lines graphs there is thus no way of knowing if other graph types (e.g., bar graphs) would yield similar results. Study 1, though deliberately non-experimental, also ignored potential order effects—each student began the interview by seeing the self-focused graph. This would have to be accounted for in an experimental design. Study 2 used only three of the five graphs in Study 1. While this preserved sample size for quantitative analysis, this also limited the types of inferences that would be made about graphs in general.

Aside from being listed across forms of visualizations, there were also necessary limitations *within* forms of visualizations. Line graphs have the potential to depict various types of academic scenarios, and the ones chosen for this study were artificial; 4 of 5 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 necessarily yield different interpretations.

Another limitation is the fact that neither study was conducted within an authentic learning analytics application environment, or an authentic learning environment. Both studies relied 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. The nature of these differences could not be captured by either Study 1 or Study 2.

Future Directions

This dissertation represents the starting point for a program of research that has various branches—each equally important when it comes to understanding the role representations play in terms of student motivation. Future work will likely focus on studying other forms of visualizations of academic information. A possible starting point would be to replicate both Study 1 and Study 2 using bar graphs, since the graph comprehension literature also suggests that bar graphs are well suited to display comparative information (Shah & Freedman, 2009).

Using “real” data in future research is also important. This data can be either be drawn from institutional sources, or it can be generated in real-time via a survey instrument that builds visualizations “on the fly” after respondents answer a set of questions. The former would lend itself to a correlational or qualitative design. Participants in such a study could, for example, reflect on their progress over time as communicated by graphs during interviews. Another approach would be to use the MISQ could also be used to capture their general attitudes about how their information is presented, these results could then be correlated with their responses to other graphs that use their actual data. Such a design might parallel the design of Study 2.

Perhaps the most compelling future direction for this work, however, is to use an experimental design that also generates visualizations on the fly. This would enable testing for actual differences as well as calculate effect sizes; experimental groups could be balanced on relevant variables, such as their scores on the PVIS and PAIS scales, as well as gender and at-risk status. This would enable the strait forward analysis of specific visualizations that show academic scenarios. Such an experiment could also, in theory, be done via survey, rather than in the lab.

Eye-tracking is another tool that could inform future work. It might be the case, for example, that students high in PVIS focus on certain parts of visualizations more intently, or more frequently. These fixations might vary by course and by achievement scenario. Data from such a study would be well suited to inform the design of visualizations utilized by learning analytics applications.

Conclusion

If effectively designed, graphs and/or other 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 applications 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 applications 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 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 dissertation is a first 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, students interpret them in complex ways. This work is messy, necessary, and exciting.

Appendices

Appendix A: Representations

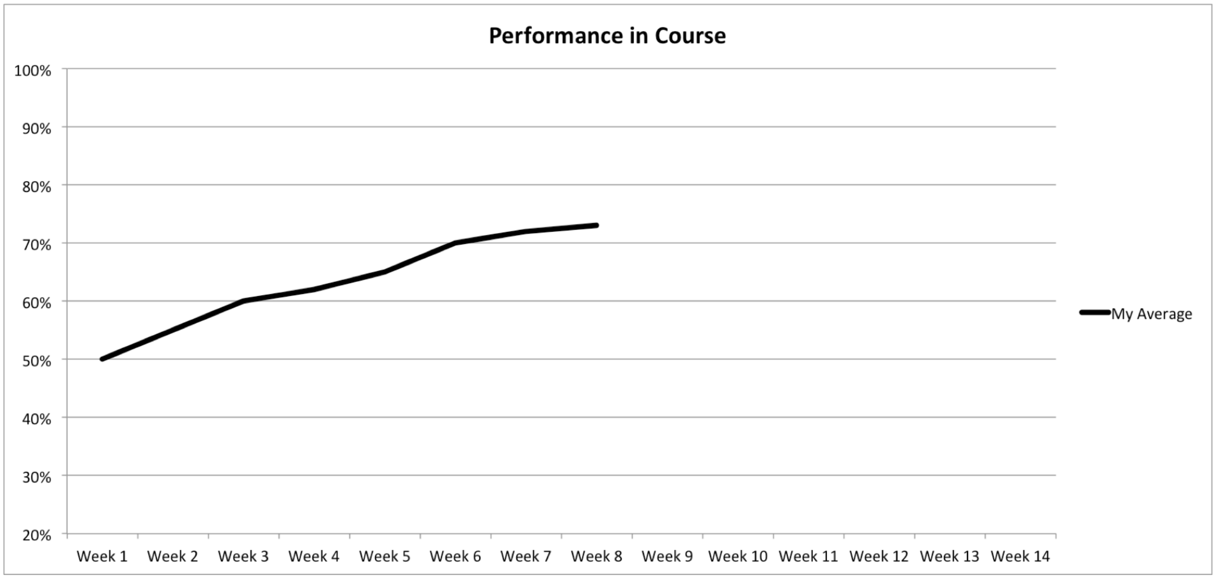


Figure 40. Line Graph 1a (large); upward trend, self-focused information

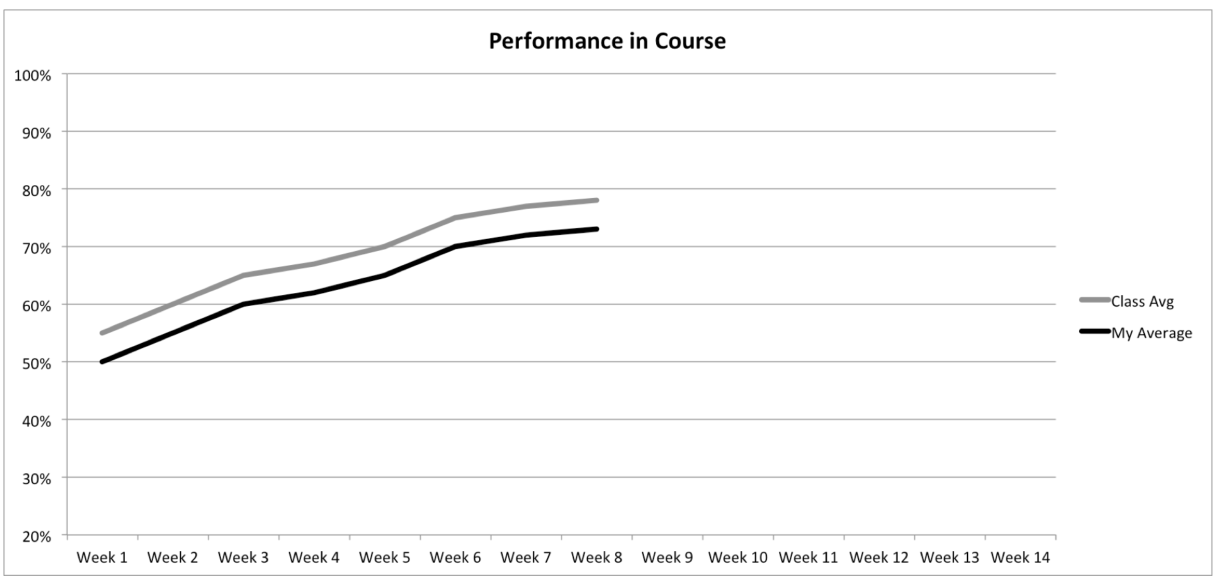


Figure 41. Line Graph 1b (large); upward trend, comparative information

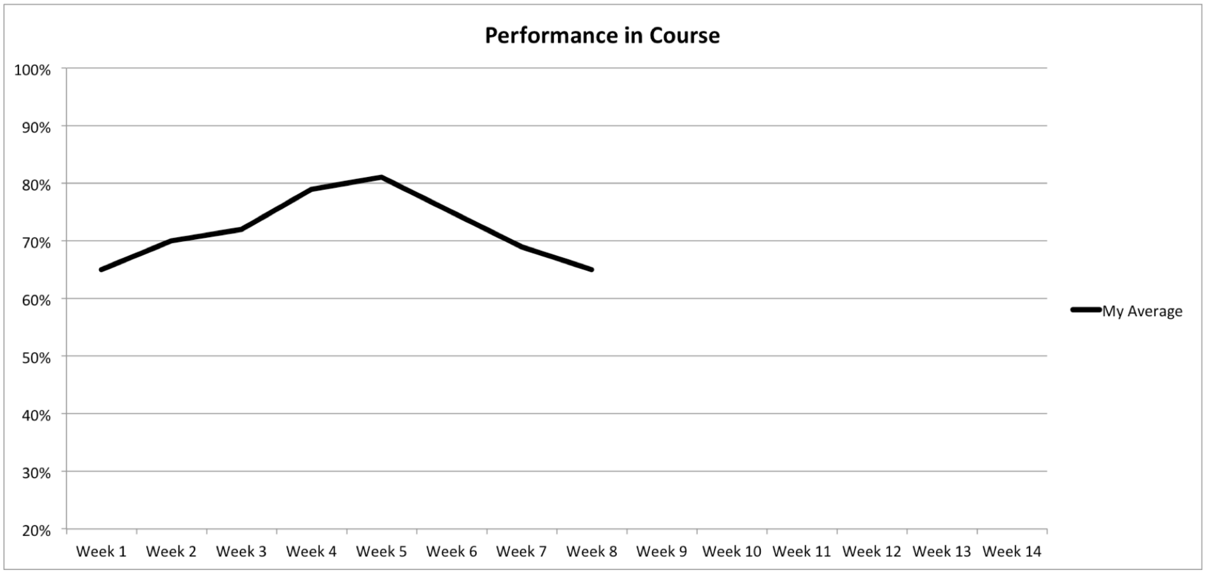


Figure 42. Line Graph 2a (large); downward trend, self-focused information

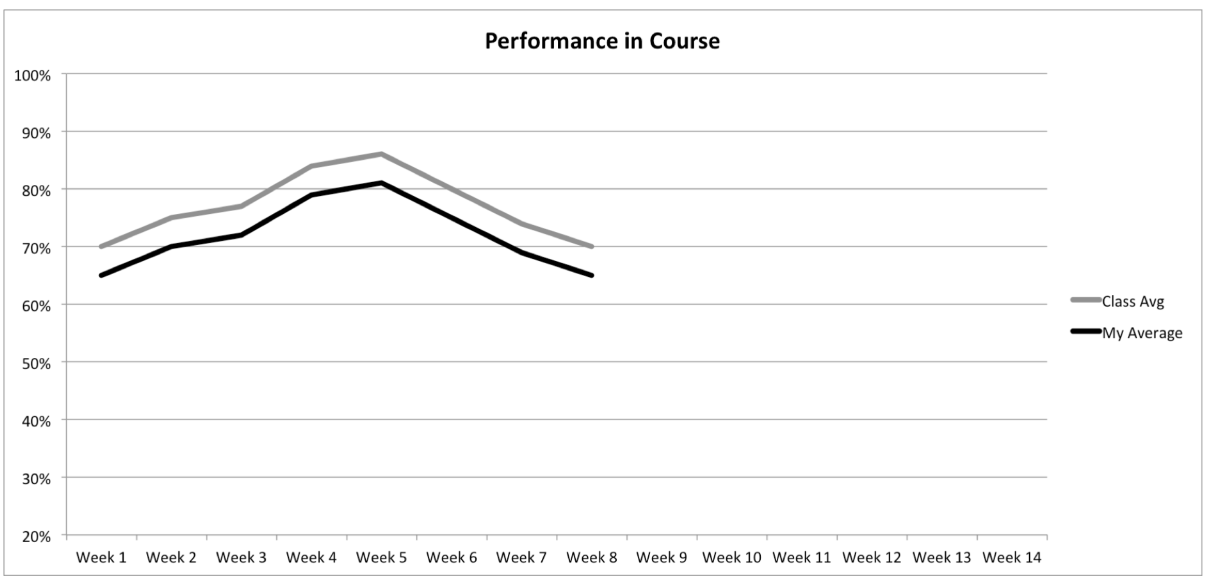


Figure 43. Line Graph 2b (large); downward trend, comparative information

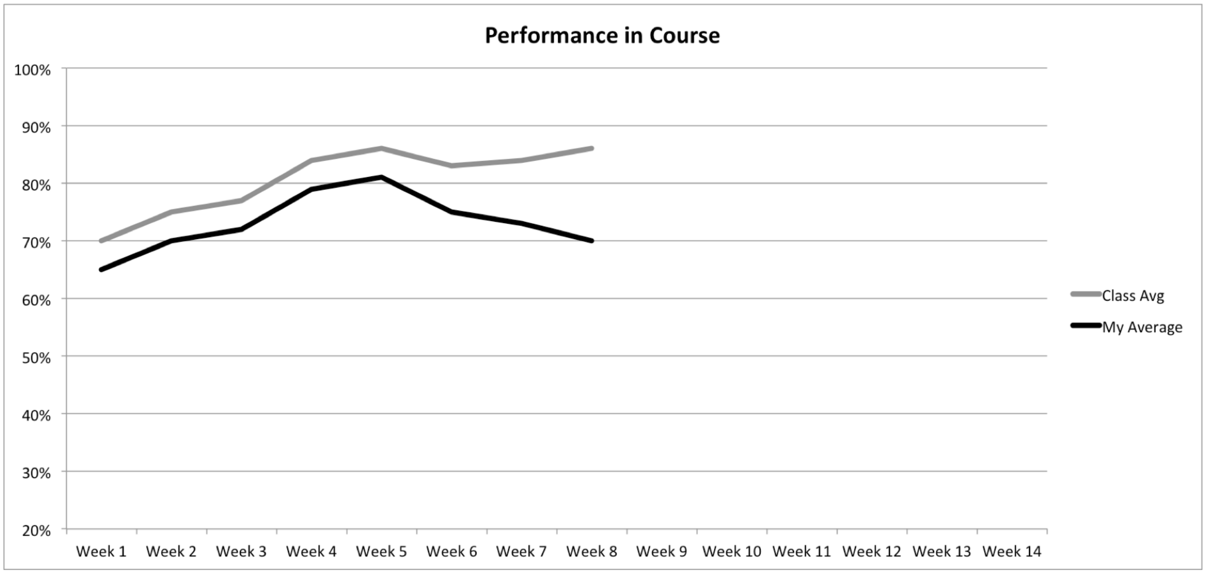


Figure 44. Line Graph 2c (large); divergent trend, comparative information

Appendix B: Motivation Items

PALS (Midgley et al., 2000)

Please mark the number that indicates what you think in response to each statement below

1: Not at all true 3: Neither true nor untrue 5: Very true

Mastery

It's important to me that I learn a lot of new concepts in this class.

One of my goals is to master a lot of new skills in this class.

It's important to me that I improve my skills in this class.

One of my goals in this class is to learn as much as I can.

It's important to me that I thoroughly understand my class work.

Performance-Approach

It's important to me that other students in this class think I am good at my class work.

It's important to me that I look smart compared to others in this class.

One of my goals is to look smart in comparison to the other students in this class.

One of my goals is to show others in this class that I'm good at my class work.

One of my goals is to show others that class work is easy for me.

Performance-Avoid

It's important to me that I don't look stupid in this class.

One of my goals is to keep others in this class from thinking I'm not smart.

It's important to me that my teacher doesn't think that I know less than others in this class.

One of my goals in this class is to avoid looking like I have trouble doing the work.

MSLQ (Pintrich & de Groot, 1990a)

Please mark the number that indicates what you think in response to each statement below

1: Not at all true of me 7: Very true of me

Self-Efficacy

2. Compared with other students in this class I expect to do well.

7. I'm certain I can understand the ideas taught in this course.

10. I expect to do very well in this class.

11. Compared with others in this class, I think I'm a good student.

13. I am sure I can do an excellent job on the problems and tasks assigned for this class.

15. I think I will receive a good grade in this class.

20. My study skills are excellent compared with others in this class.

22. Compared with other students in this class I think I know a great deal about the subject.

23. I know that I will be able to learn the material for this class.

New Instrument Pilot Items

Please mark the number that indicates what you think in response to each statement below

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3)

A little true of me (4) Very true of me (5)

Mastery

It's important for me to see information that only shows my progress in class. (imgo1)

I strongly prefer to see information that shows that I have learned a lot of new skills in class. (imgo2)

It's important for me to see information that shows that I have I improved my skills in class. (imgo3)

Information shown to me about my class should only be about how I am doing, not how others are doing. (imgo4)

Seeing information about how other students are doing would interfere with my learning. (imgo5)

Only seeing information about my performance in class helps me be learn class material. (imgo6)

I don't like information that compares my academic performance to anyone else. (imgo7)

I don't need to see information about other student's progress in class because it doesn't really matter. (imgo8)

Information that only shows my own progress helps me focus on improving myself. (imgo9)

Performance-Approach

It's important for me to see information that shows me doing better than other students in class. (pa1)

It's important for me to see information that shows that I am smart compared to others in class. (pa2)

Select not at all true of me (comp check)

I strongly prefer to see information that shows me being ahead of other students in class. (pa3)

Information shown to me about my class should show that I am doing better than others. (pa4)

Seeing information about how I'm doing helps me stay ahead of other students. (pa5)

It's important for me to see information that shows me doing better than others. (pa6)

I work harder if I see information that shows me ahead of other students. (pa7)

One of my goals in class is to see information that shows me doing better than others. (pa8)

I want to see information that shows me beating other students. (pa9)

Performance-Avoid

I don’t want to see information that makes me look stupid. (pv1)

It’s important for me to not see information that shows me knowing less than others in class. (pv2)

One of my goals in class is to avoid seeing information that implies that I have trouble doing the work. (pv3)

I strongly prefer seeing information that keeps others in this class from thinking I’m not smart. (pv4)

I don’t want to see information that shows other students doing better than me. (pv5)

It's important to me to not be discouraged by seeing information of others doing better than me. (pv6)

Select very true of me (pv7)

I don't need to see information that shows me doing below the average. (pv7)

It's important to me to not see information that shows me doing worse than other students. (pv8)

I get stressed out when I see information that shows others doing better than me. (pv9)

I avoid information that shows me doing worse than others because it makes me feel dumb. (pv10)

Appendix C: Interview Protocol

Interview Protocol Revised

> My name is Stephen, and I will be conducting the interview today. This interview is a part of a larger project that aims to build tools that help students succeed in their coursework.
>
> The purpose of today's interview is to learn a bit more about how your academic successes and setbacks have been—and can be—represented to you over your academic career. I will also utilize an eye-tracker during this interview.
>
> Your responses will remain confidential, and this interview will not be shared with anyone, so feel free to be as candid as you would like. Is it ok if I we record this conversation?

Academic Self-Concept, Self-Efficacy, & role within CSP

What sort of student do you consider yourself?

What does it mean to be a [their answer] student?

Which experiences have led you to consider yourself [their answer] of student?

Were you the same type of student before attending the University of Michigan?

> Why/why not?
>
> How can you tell?

In general, what motivates you as a learner?

> Why is that?

How do you generally expect to do in the courses you take?

> Is that true for any type of course?
>
> Tell me more

History of Representations

Tell me about a time that you knew, beyond a doubt, that you did poorly in a class.

How did you know you were doing poorly?

Which class was it?

Tell me about a time that you knew, beyond a doubt, that you did well on a class

How did you know?

Which class was it?

Downward Trajectory Representations (2abc)

Pretend, for a moment, that you are taking a course that you are likely to take in the future.

Do you have a course in mind?
[Wait for response]

Great, what course did you choose?
[Write down course]

What are your goals for that course?

What would motivate you to accomplish those goals?
[Write down course]

I am now going to show you at a graph of how you are doing in that course. As you will see in a moment, the course is about halfway done.

I am now going to show you a few graphs on this screen, but before I do you'll need to go through a quick calibration procedure for the eye-tracking device.
[Student calibrates—approx. 10-15sec]

Great! Thank you for that; the device is now calibrated. For these next questions it's ok for you to look away from the screen sometimes, but please try to keep your eyes on the screen as you answer the following questions.

Show graph 2a, on screen

Here is the first graph (10 second, force move on)

How are you doing in the course ?

Which part of the graph that makes you think that?

What was the first thing you noticed about the graph?

Why was that noticeable?

How would you explain this graph to one of your peers?

Using the mouse curser, can you to trace a line through week 14, to show me how you think you'll do by the end?

How did you decide what line to trace?

Show graph 2b, on screen

I am now going to show you another graph for the same course.

(10 second, force move on)

Compared to the first graph, does this graph say that you are doing the same, better, or worse in the course?

Which part of the graph that makes you think that?

How are other students doing in that course?

What was the first thing you noticed about the graph?

Why was that noticeable?

How would you explain this graph to one of your peers?

Using the mouse curser, can you to trace a line through week 14, to show me how you think you'll do by the end?

How did you decide what line to trace?

Show graph 2c, on screen

I am now going to show you third graph for the same course.

(10 second, force move on)

Compared to the previous two graphs, does this graph say that you are doing the same, better, or worse in the course?

Which part of the graph that makes you think that?

How are other students doing in that course?

What was the first thing you noticed about the graph?

Why was that noticeable?

How would you explain this graph to one of your peers?

Using the mouse curser, can you to trace a line through week 14, to show me how you think you'll do by the end?

How did you decide what line to trace?

Show graph 2a, 2b, 2c, on screen

Here are all three graphs. The following questions will ask you to compare them to one another.

Which graph do you believe would make you more motivated to do well in the course?

Why? What's motivating about it?

Is there anything you found helpful about how the information was presented in one or more of the, graphs?

Is there anything you didn't find helpful?

Upward Trend Representations (1ab)

The following graphs I am about to show you are still about the same course, but they depict different information.

Please keep the course you chose in mind, and answer the following questions based solely on these new graphs.

Show graph 1a, on screen

Here is the first graph (10 second, force move on)

How are you doing in the course ?

Which part of the graph that makes you think that?

What was the first thing you noticed about the graph?

Why was that noticeable?

How would you explain this graph to one of your peers?

Using the mouse curser, can you to trace a line through week 14, to show me how you think you'll do by the end?

How did you decide what line to trace?

Show graph 1b, on screen

Here is another graph for the same course.

(10 second, force move on)

Compared to the previous graph, does this graph say that you are doing the same, better, or worse in the course?

> Which part of the graph that makes you think that?
>
> How are other students doing in that course?

What was the first thing you noticed about the graph?

> Why was that noticeable?

How would you explain this graph to one of your peers?

Using the mouse curser, can you to trace a line through week 14, to show me how you think you'll do by the end?

> How did you decide what line to trace?

Show graph 1a, and 1b

Here are the two previous graphs. The following questions will ask you to compare them to one another.

Which graph do you believe would make you more motivated to do well in the course?

Why? What's motivating about it?

Is there anything you found helpful about how the information was presented in one or more of the, graphs?

Is there anything you didn't find helpful?

Wrap up

Here are all five graphs again.

Aside from what these graphs show, what other information about your performance in the course would it be helpful to see?

Tell me more

Which of the five graphs that I've shown you do you feel to be most representative of the type of student you are?

Why?

Appendix D: Survey Instrument for Part 2

How old are you?

______ Age (1)

If Age Is Greater Than 25, Then Skip To End of Block

Are you a college student?

Yes (1)

No (2)

If No Is Selected, Then Skip To End of Block

In this study you will be asked a series of questions about how you approach academic work. There are no foreseeable risks of participation. Others may benefit from the knowledge obtained in this study. You must be 18 or older to participate in this study. Participation is completely voluntary. Participation is anonymous and you will not be required to disclose your name. After the study is completed, the data will be stored at the University of Michigan in a secure location, and analyzed. If you have questions about this research study, you may contact:

Stephen Aguilar

610 E University Ave

Ann Arbor, MI 48109

(734) 764-9470

aguilars@umich.edu

The University of Michigan Institutional Review Board Health Sciences and Behavioral Sciences has determined that this study is exempt from IRB oversight.

I agree to participate in the study (1)

I do NOT agree to participate in this study (2)

If I do NOT agree to participate... Is Selected, Then Skip To End of Block

Which option below best describes your gender?

Male (1)

Female (2)

Other (3) ____________________

Which option below best describes your race/ethnicity?

White (1)

Hispanic or Latino (2)

Black or African American (3)

Native American or American Indian (4)

Asian/Pacific Islander (5)

Other (please indicate) (6) ____________________

Did you start college immediately following high school?

Yes (1)

No, there was a gap between high school and college (2)

Answer If Did you start college immediately following high school? No, there was a gap between high school and college Is Selected

How long was the gap between high school and college?

Less than 6 months (1)

6 months to a year (2)

1-2 years (3)

3-4 years (4)

5+ years (5)

Answer If Did you start college immediately following high school? No, there was a gap between high school and college Is Selected

Were you involved in any of the following during the gap between high school and college? (select all that apply)

Military service (1)

Religious service (2)

Full time employment (4)

Family obligations (5)

Travel (abroad or domestic) (6)

Other reason (please list) (3) ____________________

What is the name of your college, university, or other higher education institution?

Please indicate your status at the institution as of Fall 2015.

Freshman (1)

Sophomore (2)

Junior (3)

Senior (4)

Other (please indicate) (5) ____________________

Do you qualify for Federal Pell Grants?

Yes (1)

No (2)

Are you a first generation college student?

Yes (1)

No (2)

What is your current GPA? (If you're an incoming Freshman, select "Not Applicable" for cumulative GPA.)

______ High School GPA (1)

______ Previous Semester/Quarter GPA (2)

______ Cumulative GPA (3)

During the last academic term, how often did you do the following activities?

What is your intended or declared major?

During the last academic term, how often did you do the following activities?

Never (1) Once (2) Once a Month (3) 2-3 Times a Month (4)

Once a Week (5) 2-3 Times a Week (6) Daily (7)

Check your grades online (1)

Voluntarily visit office hours for help (2)

Email a professor for help (3)

Email a teaching aid for help (4)

Email your advisor (5)

Go to a study center for help (6)

Compare your grade in a class to a classmate's (7)

Compare your grade in a class to a trusted friend (8)

Compare your grade in a class to an acquaintance (9)

The following statements refer to your personal attitudes about seeing academic information about your college classes. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3)

A little true of me (4) Very true of me (5)

It’s important for me to see information that only shows my progress in class. (1)

I strongly prefer to see information that shows that I have learned a lot of new skills in class. (2)

It’s important for me to see information that shows that I have I improved my skills in class. (3)

Information shown to me about my class should only be about how I am doing, not how others are doing. (4)

Seeing information about how other students are doing would interfere with my learning. (5)

Only seeing information about my performance in class helps me be learn class material. (6)

I don’t like information that compares my academic performance to anyone else. (7)

I don’t need to see information about other student’s progress in class because it doesn’t really matter. (8)

Information that only shows my own progress helps me focus on improving myself. (9)

It’s important for me to see information that shows me doing better than other students in class. (10)

It’s important for me to see information that shows that I am smart compared to others in class. (11)

Select not at all true of me (29)

I strongly prefer to see information that shows me being ahead of other students in class. (12)

Information shown to me about my class should show that I am doing better than others. (13)

Seeing information about how I’m doing helps me stay ahead of other students. (14)

It's important for me to see information that shows me doing better than others. (15)

I work harder if I see information that shows me ahead of other students. (16)

One of my goals in class is to see information that shows me doing better than others. (17)

I want to see information that shows me beating other students. (18)

I don’t want to see information that makes me look stupid. (19)

It’s important for me to not see information that shows me knowing less than others in class. (20)

One of my goals in class is to avoid seeing information that implies that I have trouble doing the work. (21)

I strongly prefer seeing information that keeps others in this class from thinking I’m not smart. (22)

I don’t want to see information that shows other students doing better than me. (23)

It's important to me to not be discouraged by seeing information of others doing better than me. (24)

Select very true of me (30)

I don't need to see information that shows me doing below the average. (25)

It's important to me to not see information that shows me doing worse than other students. (26)

I get stressed out when I see information that shows others doing better than me. (27)

I avoid information that shows me doing worse than others because it makes me feel dumb. (28)

[Begin random block assignment. Respondents took either Block 1, Block 2, or Block 3]

Block 1

What is an important course that you plan to take in the future?

Why is ${q://QID49/ChoiceTextEntryValue} important? (You can choose more than one answer.)

I need it for my major (1)

I really want to learn the material it teaches (2)

I need it to learn the material it teaches to get a good job in a related field (3)

I need it for graduate school (4)

It is important for my identity (5)

Other (please specify) (6) ____________________

The following questions refer to ${q://QID49/ChoiceTextEntryValue}. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

Compared with other students in this class I expect to do well (4)

I'm certain I can understand the ideas taught in this course (10)

I expect to do very well in this class. (11)

Compared with others in this class, I think I'm a good student. (12)

I am sure I can do an excellent job on the problems and tasks assigned for this class (13)

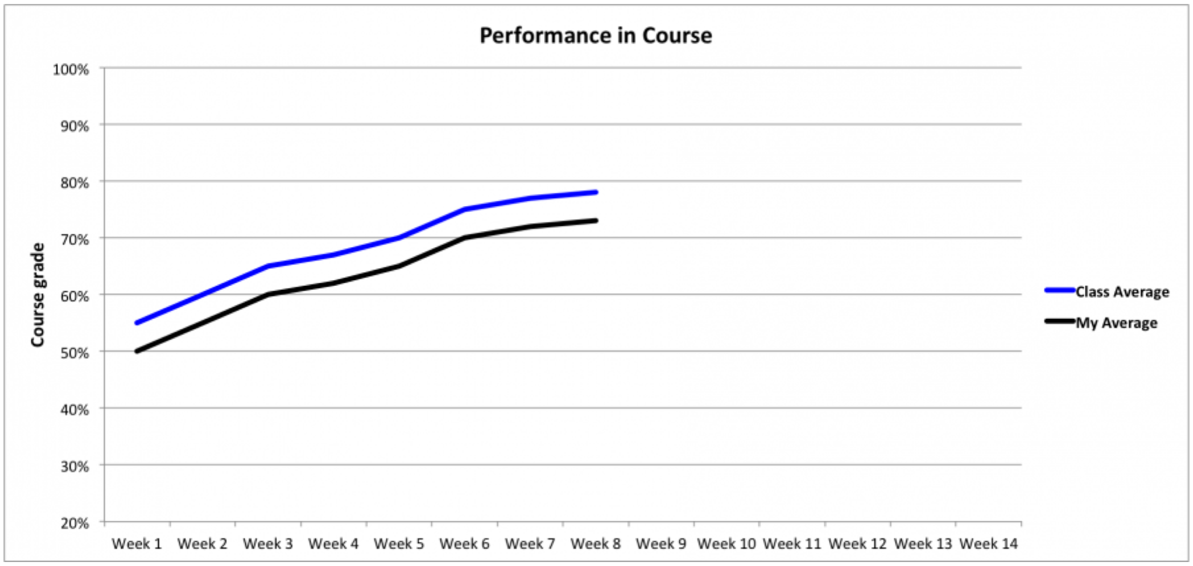
I think I will receive a good grade in this class. (14)

My study skills are excellent compared with others in this class. (15)

Compared with other students in this class I think I know a great deal about the subject. (16)

I know that I will be able to learn the material for this class. (1)

Assume that the graph below depicts your actual performance in ${q://QID49/ChoiceTextEntryValue} after 8 weeks of class.



The following questions refer to the graph above. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

When I see my performance depicted in this way it...

...makes me angry (4)

...makes me sad (5)

...makes me happy (6)

...upsets me (3)

...makes me feel curious (2)

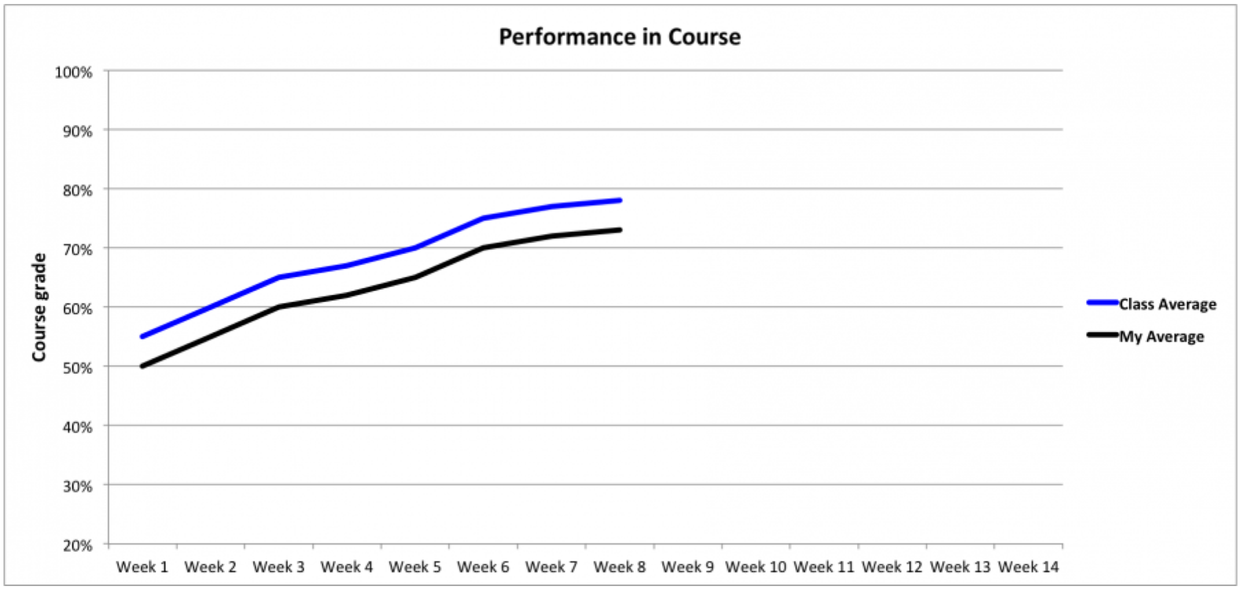
...makes me proud (1)

...makes me anxious (8)

...makes me feel content (7)

...select a little true of me (10)

If ...select a little true of ... Is Not Selected, Then Skip To End of Block



Below are some possible causes for why you are consistently below the class average in ${q://QID49/ChoiceTextEntryValue}.

Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1)   Not very true of me (2)   Neither true nor untrue of me (3)

A little true of me (4)   Very true of me (5)

I'm not very good at this sort of course (1)

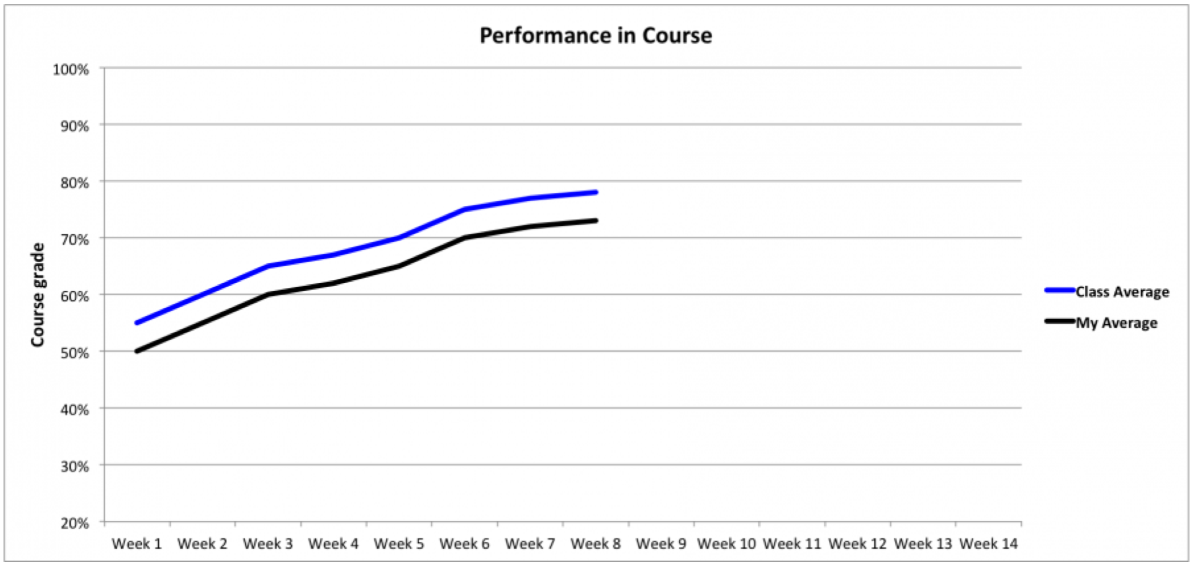
The professor was a difficult grader (2)

I always have bad luck with these types of courses (3)

This has been an unusually difficult term for me (4)

I could have studied more, but I didn't (5)

Click on the part of the graph you feel communicates the most important information.



Block 2

What is an important course that you plan to take in the future?

Why is ${q://QID87/ChoiceTextEntryValue} important? (You can choose more than one answer.)

I need it for my major (1)

I really want to learn the material it teaches (2)

I need it to learn the material it teaches to get a good job in a related field (3)

I need it for graduate school (4)

It is important for my identity (5)

Other (please specify) (6) ____________________

The following questions refer to ${q://QID87/ChoiceTextEntryValue}. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

Compared with other students in this class I expect to do well (4)

I'm certain I can understand the ideas taught in this course (10)

I expect to do very well in this class. (11)

Compared with others in this class, I think I'm a good student. (12)

I am sure I can do an excellent job on the problems and tasks assigned for this class (13)

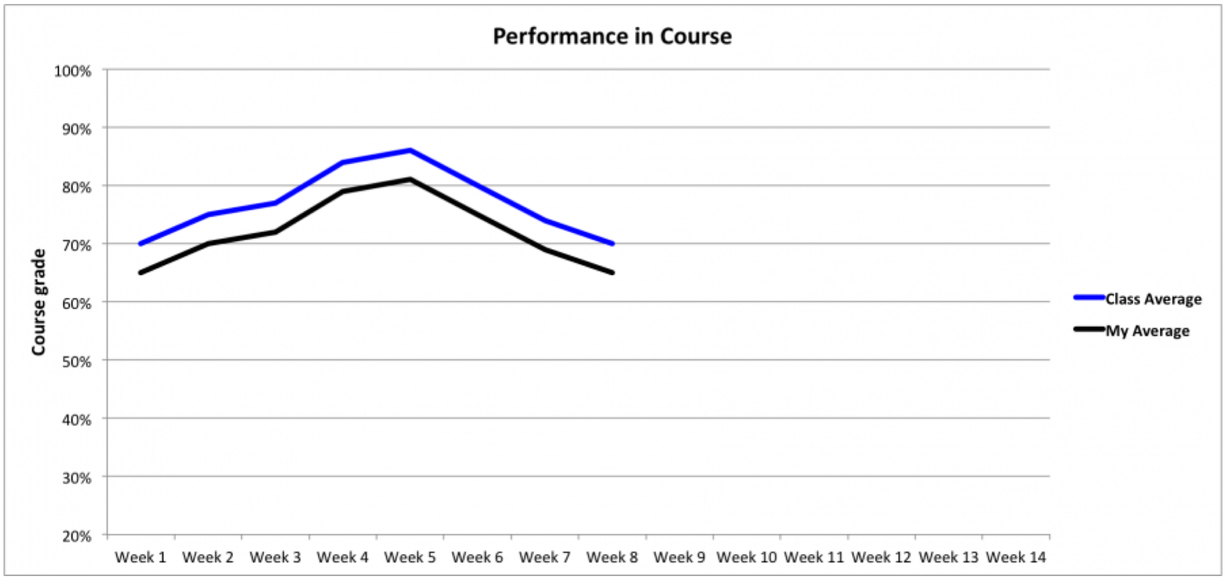
I think I will receive a good grade in this class. (14)

My study skills are excellent compared with others in this class. (15)

Compared with other students in this class I think I know a great deal about the subject. (16)

I know that I will be able to learn the material for this class. (1)

Assume that the graph below depicts your actual performance in ${q://QID87/ChoiceTextEntryValue} after 8 weeks of class.



The following questions refer to the graph above. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

When I see my performance depicted in this way it...

...makes me angry (4)

...makes me sad (5)

...makes me happy (6)

...upsets me (3)

...makes me feel curious (2)

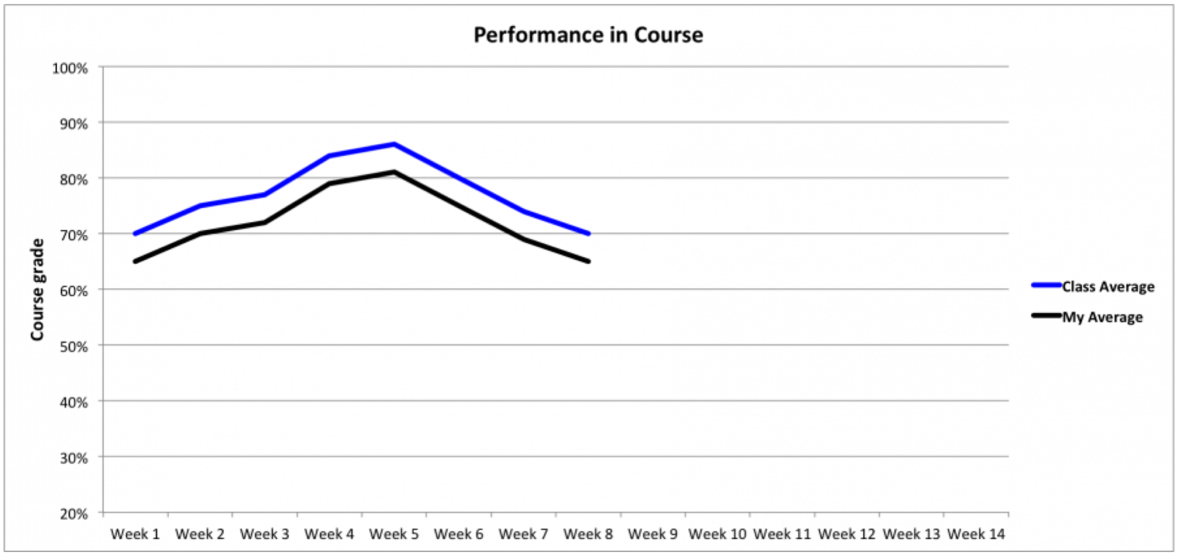
...makes me proud (1)

...makes me anxious (8)

...makes me feel content (7)

...select a little true of me (10)

If …select a little true of … Is Not Selected, Then Skip To End of Block



Below are some possible causes for why you are consistently below the class average in ${q://QID87/ChoiceTextEntryValue}.

Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

I'm not very good at this sort of course (1)

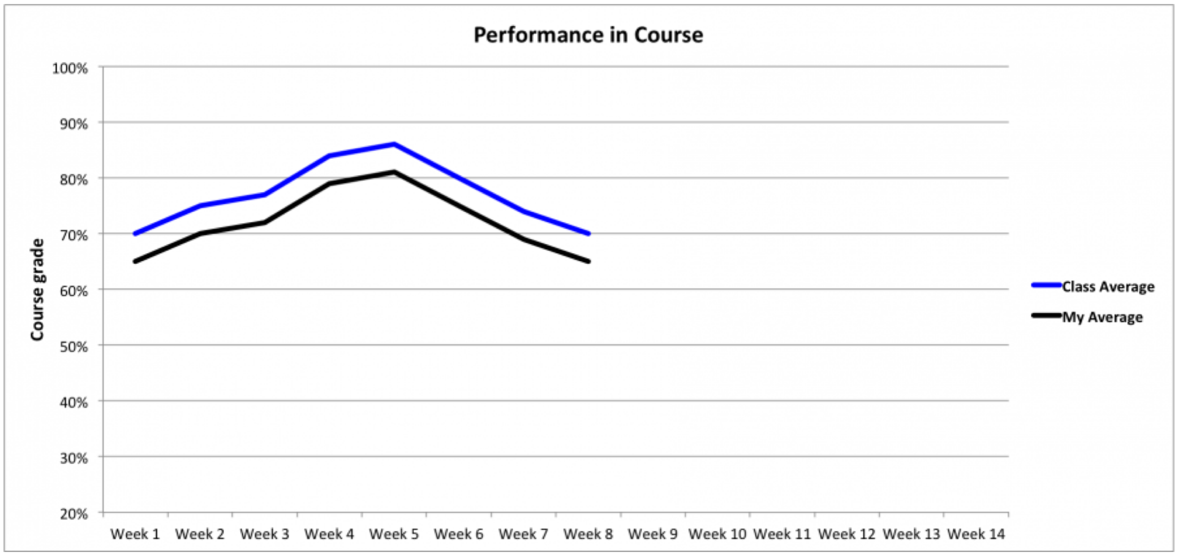
The professor was a difficult grader (2)

I always have bad luck with these types of courses (3)

This has been an unusually difficult term for me (4)

I could have studied more, but I didn't (5)

Click on the part of the graph you feel communicates the most important information.



Block 3

What is an important course that you plan to take in the future?

Why is ${q://QID96/ChoiceTextEntryValue} important? (You can choose more than one answer.)

I need it for my major (1)

I really want to learn the material it teaches (2)

I need it to learn the material it teaches to get a good job in a related field (3)

I need it for graduate school (4)

It is important for my identity (5)

Other (please specify) (6) ____________________

The following questions refer to ${q://QID96/ChoiceTextEntryValue}. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

Compared with other students in this class I expect to do well (4)

I'm certain I can understand the ideas taught in this course (10)

I expect to do very well in this class. (11)

Compared with others in this class, I think I'm a good student. (12)

I am sure I can do an excellent job on the problems and tasks assigned for this class (13)

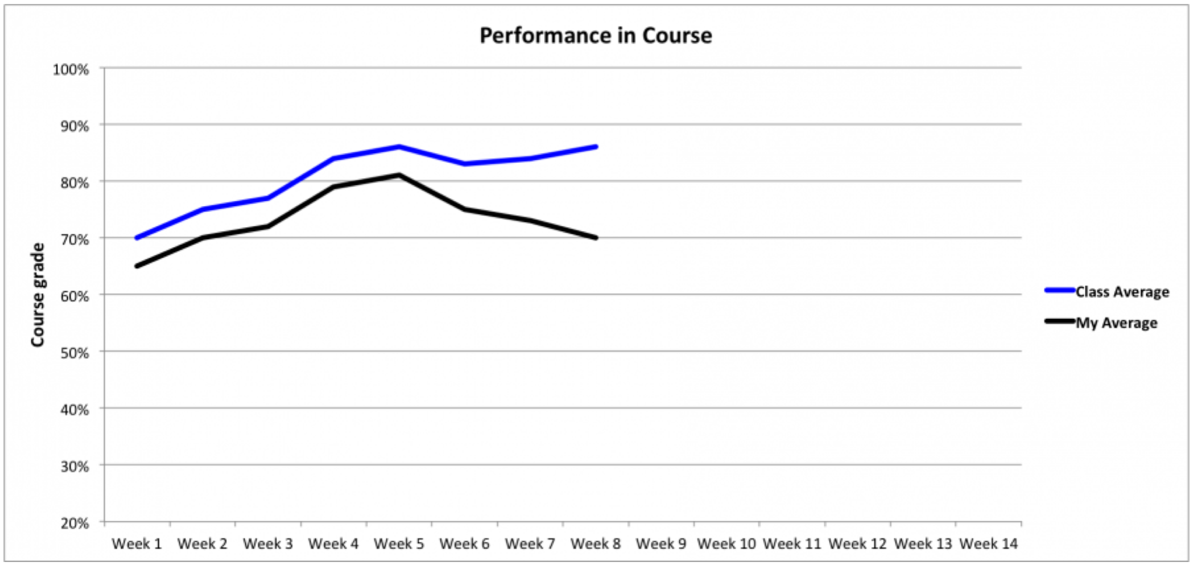
I think I will receive a good grade in this class. (14)

My study skills are excellent compared with others in this class. (15)

Compared with other students in this class I think I know a great deal about the subject. (16)

I know that I will be able to learn the material for this class. (1)

Assume that the graph below depicts your actual performance in ${q://QID96/ChoiceTextEntryValue} after 8 weeks of class.



The following questions refer to the graph above. Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

When I see my performance depicted in this way it...

...makes me angry (4)

...makes me sad (5)

...makes me happy (6)

...upsets me (3)

...makes me feel curious (2)

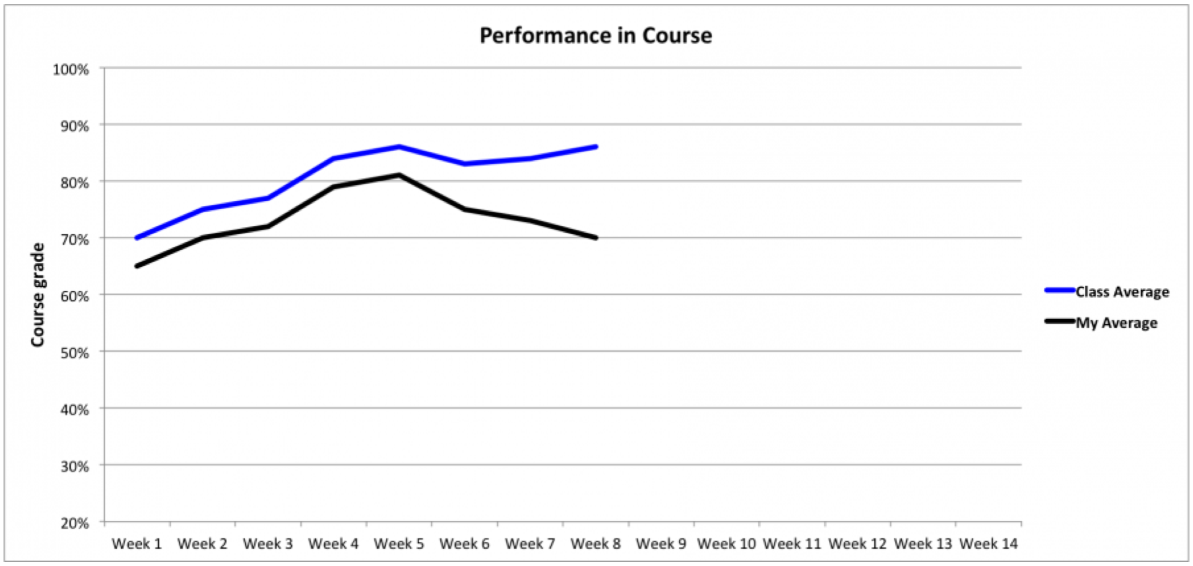
...makes me proud (1)

...makes me anxious (8)

...makes me feel content (7)

...select a little true of me (10)

If ...select a little true of ... Is Not Selected, Then Skip To End of Block



Below are some possible causes for why you are consistently below the class average in ${q://QID96/ChoiceTextEntryValue}.

Please indicate the extent to which each of the following statements is true for you:

Not at all true of me (1) Not very true of me (2) Neither true nor untrue of me (3) A little true of me (4) Very true of me (5)

I'm not very good at this sort of course (1)

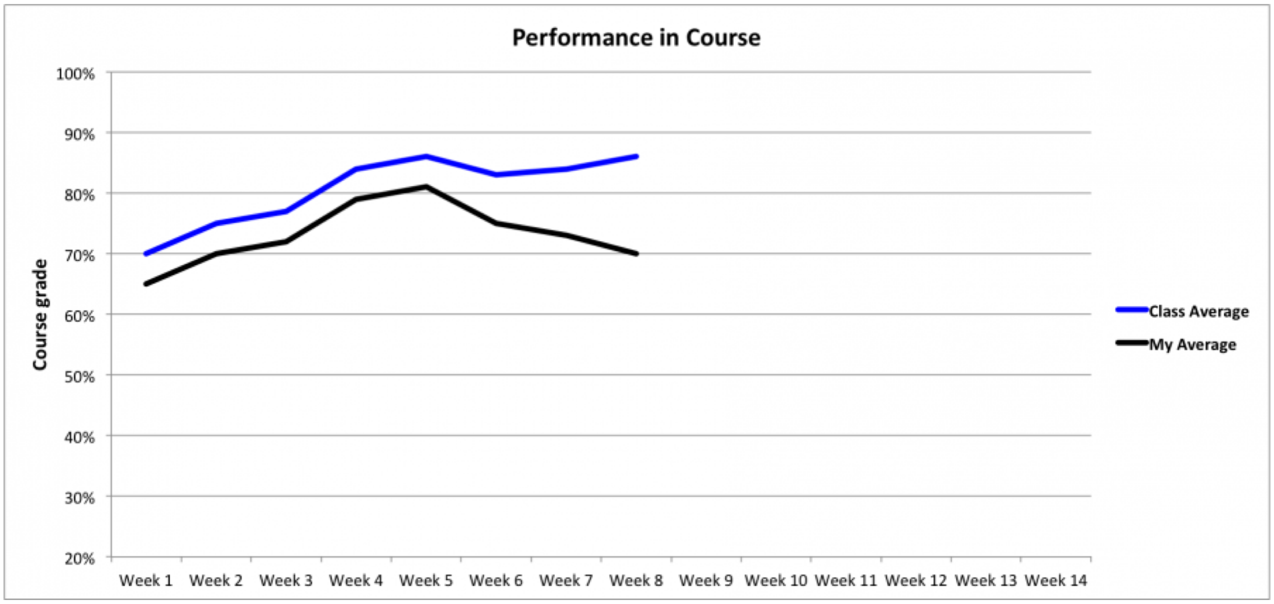
The professor was a difficult grader (2)

I always have bad luck with these types of courses (3)

This has been an unusually difficult term for me (4)

I could have studied more, but I didn't (5)

Click on the part of the graph you feel communicates the most important information.



Appendix E: MISQ Instrument (Hypothetical)

Table 14. MISQ Instrument, Means, SD, Min, Max

Survey Items	ID	Mean	SD	Min	Max
Mastery Information Seeking Orientation					
It's important for me to only see information that shows my progress in class.	imgo1	3.33	1.20	1.00	5.00
I strongly prefer to see information that proves that I have learned a lot of new skills in class.	imgo2	4.06	0.96	1.00	5.00
It's important for me to see information that shows that I have I improved my skills in class.	imgo3	4.12	0.99	1.00	5.00
Information shown to me about my class should only be about how I am doing, not how others are doing.	imgo4	3.35	1.26	1.00	5.00
Seeing information about how other students are doing in class interferes with my learning.	imgo5	2.58	1.21	1.00	5.00
Only seeing information about how I am doing in class helps me learn better.	imgo6	3.07	1.15	1.00	5.00
I don't like information that compares my academic performance to anyone else.	imgo7	3.05	1.26	1.00	5.00
I don't need to see information about other student's progress in class because it doesn't really matter.	imgo8	3.29	1.26	1.00	5.00
Information that only shows my own progress helps me focus on improving myself.	imgo9	3.66	1.13	1.00	5.00
Performance-Approach Information Seeking Orientation					
It's important for me to see information that shows me doing better than other students in class.	ipa1	2.98	1.18	1.00	5.00
It's important for me to see information that shows that I am smart compared to others in class.	ipa2	2.99	1.22	1.00	5.00
I strongly prefer to see information that shows me being ahead of other students in class.	ipa3	3.23	1.25	1.00	5.00
Information shown to me about my class should show that I am doing better than others.	ipa4	2.89	1.14	1.00	5.00
Seeing information about how I'm doing helps me stay ahead of other students.	ipa5	3.56	1.06	1.00	5.00
It's important for me to see information that shows me doing better than others.	ipa6	2.94	1.21	1.00	5.00
I work harder if I see information that shows me ahead of other students.	ipa7	3.21	1.19	1.00	5.00
One of my goals in class is to see information that shows me doing better than others.	ipa8	2.85	1.24	1.00	5.00
I want to see information that shows me beating other students.	ipa9	2.97	1.25	1.00	5.00
Performance-Avoid Information Seeking Orientation					
I don't want to see information that makes me look stupid.	ipv1	3.30	1.31	1.00	5.00
It's important for me to not see information that shows me knowing less than others in class.	ipv2	2.85	1.22	1.00	5.00
One of my goals in class is to avoid seeing information that implies that I have trouble doing the work.	ipv3	2.83	1.23	1.00	5.00
I strongly prefer seeing information that keeps others from thinking I'm not smart.	ipv4	3.01	1.22	1.00	5.00
I don't want to see information that shows other students doing better than me.	ipv5	2.99	1.23	1.00	5.00
It's important to me to not be discouraged by seeing information of others doing better than me.	ipv6	3.54	1.20	1.00	5.00
I don't need to see information that shows me doing below the average.	ipv7	2.72	1.23	1.00	5.00
It is important for me to not see information that shows me doing worse than other students.	ipv8	2.83	1.18	1.00	5.00
I get stressed out when I see information that shows others doing better than me.	ipv9	3.37	1.31	1.00	5.00
I avoid information that shows me doing worse than others because it makes me feel dumb.	ipv10	2.95	1.31	1.00	5.00

Appendix F: Regression Tables for Study 2

Table 15. Motivation Measures Predicting Affect Controlling for Demographic Variables and Academic Variables: Graph 1b

	Post-Survey Measures (DV)															
	Proud		Curious		Upset		Angry		Sad		Happy		Content		Anxious	
Demographic																
Female	-.04	.23	-.15	.18	.03	.23	.01	.22	.03	.21	-.06	.23	-.09	.23	.02	.20
Pell	-.02	.24	.00	.19	.02	.23	.08	.23	.06	.22	.03	.24	.02	.24	.02	.21
First Generation	.24**	.24	-.01	.19	-.05	.23	.02	.23	-.08	.22	.27**	.24	.23*	.24	-.12	.21
Minority	-.18*	.12	.14	.10	.04	.12	-.06	.12	.16	.11	-.15	.12	-.16	.12	.14	.10
Academic																
High School GPA	.01	.22	-.10	.17	.05	.21	-.04	.21	-.06	.20	.03	.21	-.06	.22	-.01	.19
Term GPA	-.15	.35	-.26	.27	-.07	.34	.00	.33	-.11	.32	.00	.35	-.07	.35	-.09	.30
Cumulative GPA	.09	.35	.23	.28	-.01	.34	-.08	.33	.03	.32	-.05	.35	.00	.35	.11	.30
Motivation																
PA Info Seeking	-.03	.17	.17	.13	.17	.16	.11	.16	.20	.15	.05	.17	.02	.17	-.08	.14
PV Info Seeking	.13	.16	-.20*	.12	.07	.15	.23*	.15	.03	.14	.07	.16	.01	.16	.03	.13
Performance-Approach	.28*	.17	-.13	.14	-.07	.17	.17	.16	-.19	.16	.18	.17	.12	.17	-.01	.15
Performance-Avoid	-.23	.18	.11*	.14	.05	.18	-.01	.17	.10	.17	-.11	.18	-.08	.18	.22	.16
Mastery	-.01	.20	.38***	.16	.17	.19	-.01	.19	.23*	.18	-.02	.20	-.05	.20	.17	.17
Self-Efficacy	-.19	.18	.08	.14	.17	.17	.14	.17	.18	.16	-.21*	.17	-.14	.18	.24*	.15
R^2	.17		.24		.15		.21		.2		.14		.11		.21	

Notes. . *p < .05 **p < .01 ***p < .001. Variables entered into the model simultaneously. Each column represents a different regression model and standard error, respectively.

Table 16. Motivation Measures Predicting Affect Controlling for Demographic Variables and Academic Variables: Graph 2b

	Post-Survey Measures (DV)															
	Proud		Curious		Upset		Angry		Sad		Happy		Content		Anxious	
Demographic																
Female	-.05	.17	-.07	.19	.10	.16	.09	.21	.22**	.19	-.12	.17	-.19*	.21	.27**	.17
Pell	.01	.17	-.10	.20	.01	.17	.03	.21	-.02	.20	.04	.17	.09	.21	-.08	.17
First Generation	.25**	.18	.17	.21	-.10	.18	.05	.23	-.01	.21	.18*	.18	.10	.23	-.08	.19
Minority	.03	.08	.09	.09	.14	.08	-.20*	.10	.13	.09	.05	.08	.00	.10	-.01	.08
Academic																
High School GPA	.06	.13	-.13	.15	.00	.13	.05	.16	-.05	.15	.08	.13	.06	.16	.01	.13
Term GPA	-.17	.21	-.02	.25	.32*	.21	.14	.27	.34*	.25	.13	.21	.10	.27	-.12	.22
Cumulative GPA	.19	.23	.13	.26	-.17	.22	-.18	.28	-.22	.26	-.09	.22	-.17	.28	.16	.23
Motivation																
PA Info Seeking	-.11	.12	.00	.15	.02	.12	.01	.16	.05	.14	-.11	.12	.05	.16	.12	.13
PV Info Seeking	-.01	.12	-.05	.14	.07	.12	.26**	.15	.32**	.14	-.07	.12	.08	.15	.17	.12
Performance-Approach	-.02	.14	.33*	.16	.00	.14	.01	.18	-.10	.16	-.12	.14	.15	.18	-.02	.14
Performance-Avoid	.00	.15	-.46**	.17	.21	.14	.07	.18	.03	.17	.08	.15	-.12	.18	.12	.15
Mastery	-.14	.12	.13	.14	.23**	.12	-.04	.15	.08	.14	-.22*	.12	-.09	.15	.11	.12
Self-Efficacy	.07	.12	.09	.14	.15	.12	.13	.16	.01	.14	.00	.12	-.04	.16	-.14	.13
R^2	.11		.17		.32		.18		.24		.13		.11		.2	

Notes. . *p < .05 **p < .01 ***p < .001. Variables entered into the model simultaneously. Each column represents a different regression model and standard error, respectively.

Table 17. Motivation Measures Predicting Affect Controlling for Demographic Variables and Academic Variables: Graph 2c

	Post-Survey Measures (DV)															
	Proud		Curious		Upset		Angry		Sad		Happy		Content		Anxious	
Demographic																
Female	-.13	.14	-.29**	.23	.16	.19	-.04	.22	.10	.18	-.19*	.14	-.22*	.18	.18	.20
Pell	-.19	.16	-.13	.25	.14	.21	.06	.25	.14	.21	-.20	.16	-.19	.20	.12	.23
First Generation	.15	.16	-.08	.25	-.24**	.21	-.06	.25	-.27**	.21	.19	.16	.24*	.20	-.08	.23
Minority	.10	.10	.01	.16	-.16	.14	-.21*	.16	-.11	.13	-.03	.10	.04	.13	-.18	.15
Academic																
High School GPA	-.22	.16	-.16	.26	-.17	.21	-.27*	.26	-.21*	.21	-.18	.16	-.16	.21	-.03	.23
Term GPA	.21	.19	-.26	.29	.09	.25	.05	.29	.25	.24	.08	.18	.17	.24	.22	.26
Cumulative GPA	-.19	.22	.19	.35	-.04	.29	.03	.35	-.23	.29	-.12	.22	-.08	.28	-.30	.31
Motivation																
PA Info Seeking	.09	.11	.28*	.17	.13	.14	.24*	.17	.10	.14	.06	.11	-.16	.14	.30*	.15
PV Info Seeking	.12	.11	.04	.17	.11	.14	.14	.17	.22*	.14	.14	.11	.05	.14	.17	.15
Performance-Approach	-.06	.11	-.07	.17	.01	.14	.10	.17	.19	.14	.01	.11	-.04	.14	-.05	.15
Performance-Avoid	-.07	.12	-.27	.18	.09	.15	-.07	.18	-.05	.15	-.12	.12	.20	.15	-.18	.17
Mastery	-.24*	.11	.19	.17	.29**	.14	.10	.17	.23*	.14	-.22*	.10	-.14	.13	.15	.15
Self-Efficacy	.06	.11	.17	.18	.04	.15	.08	.17	.06	.14	.04	.11	.04	.14	.02	.16
R^2	.18		.27		.36		.25		.41		.19		.19		.23	

Notes. . *p < .05 **p < .01 ***p < .001. Variables entered into the model simultaneously. Each column represents a different regression model and standard error, respectively.

Table 18. Motivation Measures Predicting Attributions Controlling for Demographic Variables and Academic Variables: Graph 1b

	Attribution Measures (DV)									
	Internal		External		Stable		Unable		Controllable	
Demographic										
Female	.14	.18	.02	.21	.09	.17	.15	.19	.02	.21
Pell	.14	.19	.14	.21	.10	.18	.09	.19	.07	.22
First Generation	-.01	.19	-.18	.22	.09	.18	-.04	.19	-.02	.22
Minority	.12	.09	-.04	.11	.05	.09	-.05	.10	.09	.11
Academic										
High School GPA	-.15	.17	.00	.19	-.11	.16	.08	.17	.04	.20
Term GPA	-.16	.27	.06	.31	-.15	.26	-.02	.28	-.08	.32
Cumulative GPA	.16	.27	-.09	.31	.02	.26	-.13	.28	-.09	.32
Motivation										
PA Info Seeking	.40***	.13	.06	.15	.23*	.13	.01	.13	.26*	.15
PV Info Seeking	.04	.12	.15	.14	.15	.12	.19	.13	.00	.14
Performance-Approach	-.17	.13	-.07	.15	-.13	.13	-.23	.14	-.39**	.16
Performance-Avoid	.04	.14	.08	.16	.04	.14	.23	.15	.24	.16
Mastery	.07	.15	.01	.18	-.11	.15	.14	.16	.25	.18
Self-Efficacy	-.48***	.14	.04	.16	-.26**	.13	-.20*	.14	-.22	.16
R^2	.38		.08		.23		.19		.18	

Notes. . *p < .05 **p < .01 ***p < .001. Variables entered into the model simultaneously. Each column represents a different regression model and standard error, respectively.

Table 19. Motivation Measures Predicting Attributions Controlling for Demographic Variables and Academic Variables: Graph 2b

	Attribution Measures (DV)									
	Internal		External		Stable		Unable		Controllable	
Demographic										
Female	.04	.20	-.11	.19	.01	.20	.17	.18	.08	.21
Pell	.01	.21	.08	.20	-.10	.20	-.15	.18	-.05	.21
First Generation	.14	.22	-.10	.21	.26***	.22	-.10	.20	-.03	.23
Minority	.13	.10	.01	.09	.11	.10	.13	.09	.13	.10
Academic										
High School GPA	.03	.15	.00	.15	.00	.15	-.01	.14	.03	.16
Term GPA	.05	.26	.00	.24	-.13	.25	.07	.23	-.16	.26
Cumulative GPA	.03	.27	-.23	.26	.04	.27	-.02	.24	.06	.28
Motivation										
PA Info Seeking	.12	.15	-.05	.14	.05	.15	-.20	.13	.16	.15
PV Info Seeking	.08	.14	.33**	.14	.24*	.14	.29**	.13	.00	.15
Performance-Approach	.07	.17	.25	.16	-.06	.17	.06	.15	-.21	.17
Performance-Avoid	-.12	.18	-.18	.17	-.08	.17	.00	.16	.12	.18
Mastery	.02	.15	.01	.14	-.08	.14	.01	.13	.01	.15
Self-Efficacy	-.60***	.15	.17	.14	-.36	.15	-.07	.13	-.07	.15
R^2	.38		.22		.33		.15		.08	

Table 20. Motivation Measures Predicting Attributions Controlling for Demographic Variables and Academic Variables: Graph 2c

	Attribution Measures (DV)									
	Internal		External		Stable		Unstable		Controllable	
Demographic	.11	.23	-.12	.22	.06	.22	-.09	.23	-.14	.23
Female	.11	.27	.09	.24	-.01	.25	.02	.26	.00	.26
Pell	-.08	.26	-.18	.24	-.05	.25	-.08	.26	-.10	.26
First Generation	.04	.17	-.14	.16	.06	.16	-.08	.16	-.13	.17
Minority										
Academic										
High School GPA	-.05	.27	-.06	.25	-.11	.25	.04	.26	-.02	.26
Term GPA	.21	.31	.26	.28	.12	.29	.09	.30	-.05	.30
Cumulative GPA	-.05	.36	-.36*	.34	-.23	.35	-.31	.36	-.06	.36
Motivation										
PA Info Seeking	.05	.18	-.14	.16	-.09	.17	-.05	.17	-.09	.17
PV Info Seeking	.08	.18	-.01	.16	-.09	.17	.09	.17	.02	.17
Performance-Approach	-.10	.18	.13	.16	.17	.17	-.19	.17	-.10	.17
Performance-Avoid	.06	.19	.02	.18	.15	.18	.02	.19	.20	.19
Mastery	.03	.17	.29**	.16	.03	.17	.27*	.17	.03	.17
Self-Efficacy	-.33**	.18	-.07	.17	-.30**	.17	.04	.18	.01	.18
R^2	.17		.18		.16		.14		.08	

Notes. . *p < .05 **p < .01 ***p < .001. Variables entered into the model simultaneously. Each column represents a different regression model and standard error, respectively.

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