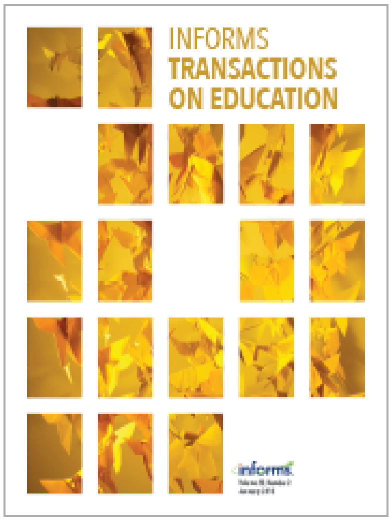

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A Comparative Study of Learning Styles and Motivational Factors in Traditional and Online Sections of a Business Course

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Abstract. Online learning has grown tremendously over the past decade. As the trend continues, it is important to understand which students are likely to choose to enroll in online courses and which factors affect their performance. This study explored the differences in motivational factors among students enrolled in online and traditional face-to-face sections of a bottleneck business course, with a focus on how these factors differentially affect performance in the two formats. Furthermore, it provided useful insights into students' decisions to select a particular course format. Results based on a sample of 146 students at a large public university showed that autonomous motivation and intrinsic value predicted students' enrollment in online courses and performance in those courses. On the other hand, performance and learning approach goal orientations predicted students' enrollment in traditional face-to-face courses and their performance in those courses. Learning styles such as reflective observation and abstract experience predicted performance, yet had no impact on course format selection. We discuss implications of these findings for student advising, course design and delivery, and broader impacts on student retention and on-time graduation.

Keywords: online courses • learning styles • motivational styles • student performance • self-regulation • intrinsic value • course format

1. Introduction

Online education has grown exponentially in the last decade in the United States and across the world. Online learning can trace its roots to distance education dating back to the 1840s, which focused on extending the educational reach of higher-education institutions. As we progress further into the information age, many institutions and schools are leveraging advances in technology to enhance their programs and expand their access to students by offering online courses and degree programs. These courses reach millions of students for whom traditional classes are not a convenient or viable option. Using videoconferencing, synchronous texting, and other approaches, schools are able to deliver such programs to students remotely without requiring them to set foot in a traditional classroom. The online education revolution has been spearheaded by massive open online courses (MOOCs)—courses designed for unlimited participation and open access via the web (Pappano 2012).

Although students usually are the ones who choose to pursue an online course due to the flexibility it offers, some research suggests that the online format is not suitable for all students (Ross and Schulz 1999). It is a well-accepted axiom throughout higher education that students have different learning styles and course design preferences and that matching student learning styles to instructor teaching style and course design can dramatically enhance the quality of the student experience and improve learning (e.g., Bristow et al. 2011). Students' success in the classroom and beyond is dependent on their ability to learn the material they are being taught. Although many factors influence a student's ability to learn, the student's learning style plays an important role (Dunn and Griggs 2000, Zapalska and Dabb 2002, Giordano and Rochford 2005). Learning style has been defined as the way in which each learner begins to concentrate on, process, and retain new and difficult information (Dunn and Dunn 1993). This concept and past research suggest that individuals differ regarding what mode of instruction or study is most effective for them (Alexandra and Moldovan 2011).

The goal of this paper is to compare learning styles and other motivational factors of students who self-selected either an online or a traditional face-to-face section of a business course and the relationship of their learning styles and motivational factors to class performance. Specifically, we focus on a "bottleneck" course on business statistics. There has been increasing pressure on universities, especially public universities, to improve student retention and reduce the time it takes students to complete their degrees in order to make more effective use of increasingly limited public funding (Crisp et al. 2018). Bottleneck courses, defined here as courses failed by a substantial portion of students (usually 20% or more), are a significant barrier to retention and graduation. Many of these courses are quantitative in nature, such as introductory-level statistics, business calculus, and college algebra,[1] and are prerequisites for upper-division courses, particularly those that require foundational quantitative skills that are needed to complete an undergraduate degree. Because bottleneck courses must be retaken until they are successfully completed, they limit students' ability to make progress toward graduation. Furthermore, because most institutions limit the number of times a failed course can be repeated, bottleneck statistics courses also may prevent some students from completing their undergraduate degrees.

If online classes could improve at least some students' performance in bottleneck statistics courses, it could be a viable strategy to reduce failure rates and improve student success. Lai and Williams (2017) discovered that, although many students in U.S. business schools struggle with their required statistics courses, technology-enhanced tools—such as those used in some online courses—that foster student engagement to facilitate their statistical learning can improve student performance. Furthermore, allowing students to self-select either online or traditional instruction may present an opportunity to better match their own learning and motivational style with the style of instruction, thereby increasing their chances of success. Fully online classes may also offer the advantage of freeing up classrooms that are required for face-to-face instruction on a regular basis that can, in turn, be used for additional instructional support for students who may be most vulnerable to failing.

Although studies on learning styles and course performance are prevalent, few have compared traditional and online formats in business disciplines, and none to our knowledge have examined the role of learning styles and motivational factors on both course selection and performance in business statistics courses. For instance, a recent study of undergraduate business students found no performance differences between a traditional and flipped-hybrid format, although self-selection was not investigated (e.g., Haughton and Kelly 2015). Moreover, student performance and course-completion rates in online courses have been found to be lower than in traditional face-to-face courses in some studies (Nelson 2006, Paden 2006, Wilson and Allen 2014), whereas others have observed no such differences (Russell 2001, Waschull 2001). Our research makes a unique contribution by investigating how distinct learning styles and motivational factors vary between online and traditional business statistics courses and how those differences are associated with performance differences. Furthermore, we investigate which of these factors predict a student's decision to enroll in a traditional or online class environment. The fact that we studied these dynamics in a bottleneck business statistics course with high failure rates enhances the importance of this research. The outcomes of this study should help faculty prepare course material, design class delivery methods, choose educational technologies, and develop sensitivity to differing student learning preferences in ways to enhance student success in bottleneck statistics courses, thereby improving student graduation rates.

The rest of the paper is organized as follows. We start with an overview of existing literature on cognitive factors that affect student performance in online and traditional courses, followed by our research questions, methods, and results. We conclude with a discussion of the practical implications, limitations, and opportunities for future research.

2. Literature Review

The level of success students achieve in their years at college has far-reaching implications for students' personal and professional lives by influencing their academic self-esteem, persistence in elected majors, and perseverance in higher education. Success in early semesters at college and experience in introductory college courses provide a solid foundation for students' continued success and retention in college. Early success also positively impacts postcollege experiences and adult life, such as career choice, personal income and level of success, and degree and nature of participation in community life (Gardner 1986, Tinto 1993). However, disaffection with and low performance in introductory college classes are serious problems at colleges and universities nationwide (Horn and Premo 1995, Horn et al. 2002). This is especially evident in introductory business, mathematics, and science courses that are considered bottleneck. Although such courses are integral components of an undergraduate education, many students who enroll in these courses achieve moderate or low levels of success in them. Poor performance in these courses results in high attrition of otherwise talented students in these areas of study (Congress of the United States, Office of Technology Assessment 1988, Gainen 1995).

Research over the last few decades identified factors that contribute to student performance in bottleneck courses in business, mathematics, and other science-based disciplines (Shotwell and Apigian

2015, Carroll and White 2017). These range from demographic factors (such as gender or ethnicity) to academic factors (such as prior academic history or GPA). For instance, African-American and Hispanic students are especially vulnerable to drop out of business, mathematics, and science-related majors (Herndon and Moore 2002, Brower and Ketterhagen 2004). Mitra and Goldstein (2015) studied academic and demographic factors that affected student performance in two bottleneck business courses and used the insights to design appropriate intervention techniques for students detected to be at risk for failing the courses.

Much work to date has compared student performance and course evaluations between face-to-face and online classes. Fewer studies have examined the differences in learning styles and preferences among students across online and traditional face-to-face delivery formats. Even as early as the late 20th century, studies compared grade distributions and performance of students in online and face-to-face classes. For instance, those enrolled in distance-education courses (cyberlearners) performed as well as or better than face-to-face students (Clark 1999, Arbaugh 2000). Since then, technology advances have led to rapid growth in the number of online degree programs and courses, with significant improvements in both the quality and delivery of such courses to foster student engagement and learning. Recently, Cavanaugh and Jacqemin (2015) conducted a large-scale study of over 5,000 courses and found little to no difference in grade-based assessment of students between face-to-face and online instructional modes. More recently, Weldy (2018) and Blau et al. (2017) compared students' perceptions and experiences in different course formats—traditional, online, and blended (combination of traditional and online)—and found that students usually prefer the traditional course format over the other two. These mixed results indicate that further research is needed to understand whether some students may be more motivated to perform in either traditional or online formats.

2.1. Learning Styles

Many students choose classes in an online format because it offers them greater flexibility to juggle school with work, social, and other commitments in their daily lives. However, research indicates that online classes may be best suited for students who are self-motivated, are self-disciplined, and have effective time-management skills (McEwan 2001, Huber and Lowry 2003). This suggests that students who lack these characteristics yet enroll in online courses may struggle and subsequently drop these courses, delaying their degree completion and graduation—a problem that is likely exacerbated in bottleneck business statistics courses that already have relatively high failure rates. It is thus essential that instructors have knowledge of students' learning styles, behavior, and motivational preferences in order to design and deliver effective instruction for a diverse group of students (Drennan et al. 2005, Lo and Shu 2005).

Individuals learn in different ways, like watching, listening, questioning, doing, and helping others to learn (Rogers and Frieberg 1994). Individuals process information differently because of distinct cognitive and learning styles and exposure to a variety of learning environments and experiences (Scarr 1992, Cassidy 2004). An individual's learning style will affect how they process information during learning and thinking, thereby impacting learning effectiveness and efficiency (Bencheva 2010). One of the most broadly known learning style inventories in education research is *Kolb's Learning Style Inventory* (*LSI*) (Kolb 1981, 1986), which we focus on in our study. Building on earlier work, the LSI posits that learning is a four-stage circular process and classifies learners as convergers, divergers, assimilators, and accommodators. Each stage correspond to a learning style: (1) concrete experience (CE; feeling), (2) abstract conceptualization (AC; thinking), (3) active experimentation (AE; doing), and (4) reflective observation (RO; watching). CE and RO constitute the "diverging" style of learning (rooted in divergent learning), which enables a person to look at things from different perspectives and learn by watching and viewing concrete situations (rather that doing). People with this style typically have broad interests and like to gather information. The "assimiliating" learning style is comprised of AC and RO, which utilizes a concise and logical approach via clear explanations to understand ideas and concepts rather than practical experiences. AC and AE characterize people with a "converging" learning style (rooted in convergent learning), who prefer to solve problems and find practical uses for the concepts and theories learned. Lastly, the "accommodating" learning style encompasses CE and AE and is hands-on, relying on intuition rather than logic. People with this style often use other people's analysis and adopt a practical and experiential approach. Despite the differences in these different learning styles, Kolb explains that learning is an integrated process, and effective learning occurs when an individual progresses through the entire cycle of the four stages, with each stage being mutually supportive of and feeding into the next. However, it is natural for a person to prefer a specific style.

The idea that students have different learning styles and preferences is now widely accepted (Wratcher et al. 1997). It is important that educators today are aware of these diverse learning styles in the student population. Yet not all faculty take these into account while teaching. Instructors often assume that either students who enroll in online classes possess the required learning styles or that they have the same learning preferences and styles as students in traditional classes. Hence, teaching methods adopted by instructors are not always effective across different class formats. Some studies have focused on the relationship between students' learning styles and other psychological characteristics and performance in online and blended courses (Chang et al. 2015, Cheng and Chau 2016). For instance, online students with a preference for active learning performed better in the course than those who had a different learning style (Bozionelos 1997). Other research, however, found no differences in grades, learning preferences, or styles between online and traditional students (Neuhauser 2002).

A substantial literature in business education studies the effect of learning styles on student performance. Kolb (1981) found that learning styles of over 800 managers and business graduate students varied with their undergraduate major. Other research found that finance and accounting majors prefer a convergent learning style, whereas marketing and management students were mostly experience-oriented (accommodators and divergers) (Bergevin 1993). Students in accounting, finance, marketing, and management information systems preferred an assimilator style using the Kolb LSI (Loo 2002), whereas visual and kinesthetic styles were preferred for introductory accounting students (Shoemaker and Kelly 2015). On the other hand, a study of over 400 undergraduate students in a financial management class using Kolb's LSI found that learning styles did not impact student performance (Fox and Bartholomae 1999). Fewer studies of learning styles have compared traditional and online business courses. In undergraduate business communications classes, online students' least preferred style was "authority and listening," whereas traditional students' least preferred style was "independence and reading" (Tucker 2001).

2.2. Motivational Orientations and Other Metacognitive Factors

Apart from learning styles, several other cognitive and metacognitive factors could impact student learning and performance in college-level courses. These include goal orientations, autonomous versus controlled motivational orientations, metacognitive learning strategies, and procrastination.

Goal orientations are cognitive frameworks that influence motivation in achievement settings (Elliot and Dweck 1988).Two types of goal orientations have implications for the tasks that students choose, how they approach these tasks, how they react to outcomes, and, ultimately, what they learn: (1) *learning* (*mastery*) *goals*, which focus students' attention and effort on developing and improving their competencies; and (2) *performance goals*, which focus students' attention and effort on demonstrating their competencies and outperforming their peers. Learning and performance goal orientations can be crossed with approach and avoid goals to form the 2×2 model of achievement goal orientations, which include: (i) learning approach goals (LGO), (ii) learning avoid goals (LAGO), (iii) performance approach goals (PGO), and (iv) performance avoid goals (PAGO) (e.g., and Elliot and McGregor 2001 and Kozlowski and Bell 2006). Learning avoid goals focus attention and effort on avoiding skill losses. Performance avoid goals focus on avoiding the appearance of incompetence or avoiding doing worse than one's peers. Research with college students has shown that learning approach goals predicted intrinsic interest, whereas performance approach goals predicted grades (Elliot and Church 1997, Elliot and McGregor 2001).

For students to succeed in a course, motivational factors play a significant role apart from academic background factors. Self-determination theory posits that motivation can be assessed along an intrinsic–extrinsic continuum (Deci et al. 1991, Ryan and Deci 2000). An autonomous motivational style lies toward the intrinsic end of the continuum and is characterized by self-regulated and self-determined motivation that includes task engagement and enjoyment. A controlled style lies toward the extrinsic end of the continuum and is experienced as motivation driven by external factors rather than inherent interest. In educational settings, students with an autonomous motivational style are more likely to engage in activities that enhance their learning, whereas individuals with a controlled motivational style are more inclined to focus their effort and attention on activities that can improve their grades (Black and Deci 2000, Ryan and Deci 2000).

Among other metacognitive factors that have a potential impact on student learning and academic performance, those that are most important are self-regulated learning and intrinsic value (Pintrich and De Groot 1990). Self-regulated learning may include students' metacognitive strategies for planning, monitoring, and modifying their cognition (Zimmerman and Pons 1988), their management of effort on various tasks and activities pertaining to the course and the cognitive processes they use for learning, understanding, and mastering course content. Intrinsic value is also an important component of students' own choice or interest in becoming cognitively engaged in their academic work. A study of science learners showed that both self-regulated learning and intrinsic value were positively related to students' engagement and academic performance (Pintrich and De Groot 1990).

Finally, procrastination, defined as a voluntary, irrational delay of behavior, has been found to impair individual academic and work group performance (Jiao et al. 2011, Lakshminarayan et al. 2012). Groups with the lowest levels of achievement tended to include students who procrastinated most frequently on administrative tasks and academic work. Procrastination is widely prevalent among college students across the world, and hence an important factor to consider in a comprehensive study of student success. Interventions such as stimulus control, stimulus cues, and cognitive restructuring have been successful in remediating procrastination (Rozental and Carlbring 2014).

3. Research Goals and Methods

The goal of this research is to study both differences (as is common practice) and similarities in learning styles, self-regulated learning behavior, goal orientations, and motivational factors among students enrolled in face-to-face and online sections of a bottleneck business statistics course and the relationship of these factors to course performance and enrollment. Specifically, our goal was to answer the following questions:

- Because students in traditional classes tend to expect more hands-on work and interactions than online students, do students in traditional classes rely more on concrete experience for learning and achieving success in the course?
- Because online courses tend to have less structure due to a lack of face-to-face class time, do students who enroll in such courses have higher levels of autonomous motivation, self-efficacy, and self-regulatory skills to manage their academic work by learning the material on their own? To what extent might they demonstrate variation in goal orientations?
- Given the potential learning style and motivational and metacognitive preferences expected for online students, to what extent do these factors predict student enrollment in a face-to-face versus an online course?

3.1. Study Sample

Undergraduate students enrolled in two fully online and three traditional face-to-face sections of an upper-division business statistics course in a large university in the western United States participated in the study over a 16-week semester. All sections were taught by the same instructor, and students were aware of the course format at the time of enrollment, having voluntarily enrolled in either the fully online or traditional face-to-face instructional format. Out of a total of 210 students, 146 completed a survey questionnaire voluntarily (70% response rate) via a link posted on the course website (with Institutional Review Board approval). Out of these, 98 (67%) belonged to the face-to-face sections and 48 (33%) to the online sections. Participation rates for each different class format were 77% for face-to-face (98 out of 126) and 57% for online (48 out of 84). The higher response rate for the face-to-face sections was likely due to regular verbal reminders to complete the survey from the course instructor. In contrast, regular weekly email reminders were sent to students in the online sections. The survey instrument consisted of demographic information and study and control variables as described in the next subsection.

All course sections used the same learning management system and the same course structure in terms of content, assignments, and exams. The exams for the online course sections were held on campus and proctored by the instructor just like the face-to-face sections, thus removing any bias in that respect. Furthermore, there were no significant differences among the four sections with respect to the basic demographic background of the students such as gender, age, ethnicity, overall GPA, etc. The traditional course sections used about 150 minutes of class time each week, mainly for lecture and in-class problem-solving activities, whereas the online classes required students to master the course content on their own, with on-campus meetings focused exclusively on conducting exams.

3.2. Measures

We assessed class format, learning styles, motivational styles, goal orientations, metacognitive strategies, procrastination, and class performance as the main predictor variables in this study. We coded class format (*CLASS*) as a binary variable (0 = traditional face-to-face; 1 = online). Learning styles of students were measured with a short form of Kolb's learning style inventory (Kolb 1981, 1986)—seven items for reflective observation and active experimentation (*ROAE*) and five items each for *AC* and *CE*. An example from the *ROAE* scale is "when I learn, I like to think about ideas." An example from the *AC* scale is "I learn best when I trust my hunches and feelings," and one from the *CE* scale is "when I learn, I like to watch and listen." All scales used 5 points (1 = strongly disagree, 5 = strongly agree). We measured motivational style with eight items from the self-regulated learning scale (Black and Deci 2000, Ryan and Deci 2000), four of which focus on autonomous motivation (*AUTREG*) and four on controlled motivation (*CONREG*). An example from the autonomous scale is "I would like to participate actively in class because a solid understanding of statistics is important to my intellectual growth," whereas an example from the controlled scale is "I would like to actively participate in class because I would feel proud of myself if I did well in the course" (1 = strongly disagree, 5 = strongly agree).

We measured goal orientations using a 7-point scale (1 = not at all true of me, 7 = very true of me) consisting of 12 items and four subscales, with three items each to assess *LGO*, *LAGO*, *PGO*, and *PAGO* (Elliot and McGregor 2001). An example learning approach goal item is "I want to learn as much as possible from this class." For the learning avoid goal, an example question is "I worry that I may not learn all that I possibly could in this class." A performance approach goal example question is "it is important for me to do better than other students," whereas a performance avoid goal example is "I just want to avoid doing poorly in this class."

We measured self-regulated learning strategies (*SLFREG*) with nine items from the self-regulated learning subscale of the metacognitive strategies scale (Pintrich and De Groot 1990). An example question is "before I begin studying I think about the things I will need to do to learn" (1 = not at all true of me, 7 = very true of me). Intrinsic value (*INTRVAL*) consisted of a nine-item scale, an example question being "I like what I'm learning in this class." We measured procrastination (*PROC*) using 6 items from the 16-item Tuckman procrastination scale (Tuckman 1991) with a sample question being "when I have a deadline, I wait till the last minute." For the latter two variables, the same scale as before was used (1 = strongly disagree, 5 = strongly agree).

Lastly, class performance was measured as a continuous variable based on the final course grade for each student, measured on a standard percentage grading scale (0–100).

All measurement scales demonstrated adequate reliability ($\alpha > 0.80$). We also did a factor analysis to assess the discriminant validity of the scales representing learning styles, motivational factors, self-regulated learning strategies, and goal orientations (varimax rotation, eigenvalues ≥ 1, factor loadings > 0.66, and cross-loadings < 0.4, except for two *SLFREG* items with high cross-loadings that we removed).

Control variables included *gender* (1 = female, 2 = male), *age* (categories: 18–24, 25–34, 35–44, and 45 and older), *ethnicity* (categories: White, Hispanic, African American, Asian/Pacific Islander, and Other), *first-generational college status* (1 = yes, 0 = no), *transfer status* (1 = first-time freshman, 2 = transfer student), *self-reported GPA*, and *number of hours/week working outside of school* (latter two included as continuous variables).

3.3. Statistical Analyses

We used analysis of variance (ANOVA) to explore whether statistically significant differences existed between students enrolled in face-to-face and online sections of the course with respect to the various study variables representing students' learning styles, motivational factors, self-regulated learning strategies, and goal orientations.

To assess the association of learning styles and motivational factors with course performance (measured by final course grades), we used multiple linear regression. We used logistic regression (Hosmer and Lemeshow 2000) to identify factors associated with a student's decision to enroll in either a face-to-face or an online section of the course. Analyses were performed by using IBM-SPSS Statistics, Version 23 (IBM n.d.). In all of our analyses, the threshold for determining statistical significance was $p < 0.05$. With 150 total responses, we included those responses that answered 50% or more of the study questions (to increase statistical power), yielding an overall sample size of 146.

4. Results

Descriptive statistics for the control (background) variables and study variables are shown, respectively, in Tables 1 and 2. Bivariate correlations among all the study variables, outcome variable (*final grades*), and the two continuous control variables (*GPA* and *work hours*) are included in Table 3. The results of the statistical analyses and models are presented next.

4.1. Learning Styles

Among the three different learning styles, we observed that the average values of *ROAE* were significantly higher for the online sections than the traditional sections ($p = 0.038 < 0.05$). This indicated that students in online sections tended to follow a learning style that is more geared toward reflective observation and active experimentation than students in the traditional sections. The other two learning styles, *AC* and *CE*, were not significantly different across the two course formats. Table 4 summarizes these results.

4.2. Goal Orientations

Goal orientations of students in traditional face-to-face and online sections revealed interesting patterns. Both performance and learning approach goal orientations were significantly higher for traditional students than online students (p-values: $LGO = 0.002$ and $PGO = 0.004$), indicating that traditional students were more focused on learning and performing well then online students. Avoidance goals showed no significant differences across the two formats. These results are included in Table 4.

4.3. Motivational Factors

Among the two different types of motivational styles, online students demonstrated a significantly higher level of the autonomous style, *AUTREG* ($p < 0.0001$), whereas there was no significant difference in the level of the controlled motivational style (*CONREG*) among students in course sections with different formats (Table 4). This suggests that online students

Table 1. Descriptive Statistics for Control Variables

Variables	Frequencies	Relative frequencies
Class format (n = 146)		
Face-to-face	98	67.1%
Online	48	32.9%
Gender (n = 145)		
Male	82	56.6%
Female	63	43.4%
Age (n = 145)		
18–24 years	86	59.3%
25–34 years	51	35.2%
35–44 years	5	3.4%
45 and older	3	2.1%
Ethnicity (n = 140)		
White	38	26.2%
Hispanic	34	23.4%
African American	5	3.4%
Asian/Pacific Islander	63	43.4%
Other	0	0%
First-generational status (n = 145)		
Yes	59	40.7%
No	80	55.2%
Transfer status (n = 144)		
First-time freshman	78	53.8%
Transfer student	66	46.2%
GPA	Mean = 3.12, standard deviation = 0.46	
Number of works/week working outside of school	Mean = 22.8, standard deviation = 17.9	

were much more likely to engage in activities that enhance their self-learning in keeping with expectations because such students require considerably more self-motivation and effort to master the topics on their own than traditional students who learn from in-class lectures and activities. Moreover, *CONREG* values were significantly lower than *AUTREG* values, on average ($p = 0.023$), for online students suggesting they were more focused on learning than grades. For traditional students, no such differences were observed.

4.4. Self-Regulated Learning Strategies

Among self-regulated learning strategies, intrinsic value averages were significantly higher for online students than traditional students ($p = 0.001$). The results are shown in Table 4. These observations also aligned with expectations regarding students in online sections, who typically needed a higher amount of interest in becoming cognitively engaged in their academic work in order to succeed than traditional students.

Table 2. Descriptive Statistics for Study Variables (n = 145)

Variable	Mean	Standard deviation
ROAE	4.38	0.513
AC	3.61	0.630
CE	4.28	0.510
AUTREG	4.09	0.749
CONREG	3.35	0.631
LGO	5.37	1.311
LAGO	4.80	1.442
PGO	4.77	1.303
PAGO	4.95	1.545
SLFREG	3.69	0.445
INTRVAL	3.96	0.682
PROC	2.60	0.972

4.5. Association of Learning and Motivational Styles with Course Performance

After observing the similarities and dissimilarities with respect to learning styles and motivational factors among students enrolled in different class formats for a bottleneck business statistics course, we next assessed the effect of these factors on course performance. For this, using the background demographic and academic variables as control variables, we built a multiple linear regression model using all the data that combined both traditional and online course sections. Moreover, we built two separate models for the traditional and the online sections in order to compare the association of the various factors with student performance across the two formats; in other words, to determine whether significant effects on course performance varied between the two different class environments.

The dependent variable used was the final grade in the course, reported as a percentage. For the categorical control variables, dummy variables were formed to include in the model, and the categories used

Table 3. Bivariate Correlations Among All the Continuous Variables (Study and Control) and of the Predictor Variables with the Final Grades (Outcome Variable)

	Grades	*AC*	*CE*	*ROAE*	*AUTREG*	*CONREG*	*LGO*	*LAGO*	*PGO*	*PAGO*	*SLFREG*	*INTRVL*	*PROC*	*GPA*	*Work hours*
Grades	—														
AC	−0.17	(0.87)													
CE	0.06	0.19	(0.89)												
ROAE	0.16*	0.21	0.25	(0.85)											
AUTREG	0.43**	0.21	0.30*	0.29*	(0.92)										
CONREG	0.20*	0.21	0.23	0.24	0.26	(0.94)									
LGO	0.47**	0.15	0.28*	0.27*	0.65**	0.31*	(0.90)								
LAGO	−0.03	0.05	0.03	−0.07	−0.02	0.24*	0.06	(0.82)							
PGO	0.31**	0.17	0.07	0.17	0.37**	0.40**	0.28*	0.16	(0.83)						
PAGO	−0.02	0.13	0.04	−0.10	−0.21*	0.55**	−0.02	0.33*	0.29*	(0.89)					
SLFREG	0.04	0.29	0.20	0.13	0.31*	0.30*	0.22	0.18	0.23	0.17	(0.94)				
INTRVL	0.42**	0.29*	0.33*	0.41**	0.78**	0.37**	0.26	0.02	0.31*	−0.19	−0.19	(0.86)			
PROC	−0.07	0.06	0.04	−0.08	0.001	0.16	−0.13	0.23*	0.13	0.28*	0.28*	0.03	(0.84)		
GPA	0.46**	0.10	0.18	0.12	0.25*	0.06	0.35*	−0.11	0.25*	−0.13	−0.13	0.04	−0.03	—	
Work hours	−0.39**	0.02	0.04	0.06	0.02	0.01	−0.07	0.11	−0.01	−0.11	−0.11	0.014	−0.09	−0.07	—

Note. Cronbach alpha is displayed in diagonal.
$^{*}p < 0.05$; $^{**}p < 0.01$ to denote correlations that are significantly different from zero.

were as follows: *gender* (1 = female, 0 = male), *ethnicity* (Hispanic, African American, and Asian/Pacific Islander, with White as the reference category because there were no responses in the "Other" category in the study sample), *age* (25–34, 35–44, and 45 and older, with 18–24 as the reference category), *first-generational status* (1 = yes, 0 = no), and *transfer status* (1 = transfer student, 0 = first-time freshman). *GPA*, *number of work hours/week*, and all the predictors representing learning styles, motivational factors, self-regulated learning strategies, and goal orientations were included as continuous variables. *Class format* was included as a binary variable (1 = online, 0 = face-to-face) in the first model.

4.5.1. Collinearity Issues. The variance inflation factors (VIFs) (Kutner et al. 2004, Sheather 2009) were calculated for all the independent variables, and none of them exceeded 5, which is typically used as the cut-off for determining the severity of multicollinearity present in the data (Sheather 2009). Although the correlation matrix in Table 4 showed significant correlations among some of the cognitive variables, particularly *AUTREG* and *INTRVAL*, the VIF values clearly indicate that this should not affect the regression models adversely, and all inferences therefrom should be valid. The highest VIF values were indeed obtained for *INTRVAL* and *AUTREG*, which were 3.66 and 3.07, respectively.

Table 4. Means, Standard Deviations, and ANOVA Results for the Different Study Variables Across Traditional and Online Sections of the Course (n = 145)

	Traditional face-to-face		Online		
Variables	Mean	SD	Mean	SD	p
Learning styles					
AC	3.64	0.63	3.55	0.63	0.455
CE	4.28	0.51	4.26	0.51	0.794
ROAE	3.93	0.45	4.47	0.54	0.038*
Goal orientations					
LGO	5.61	1.22	4.88	1.38	0.002**
LAGO	4.72	1.47	4.96	1.39	0.347
PGO	4.99	1.22	4.33	1.37	0.004**
PAGO	4.82	1.59	5.20	1.43	0.166
Motivational factors					
AUTREG	3.77	0.86	4.24	0.64	<0.0001**
CONREG	3.37	0.60	3.31	0.70	0.533
Self-regulated learning					
SLFREG	3.31	0.43	3.43	0.49	0.693
INTRVAL	3.69	0.60	4.09	0.76	0.001**
PROC	2.54	0.97	2.73	0.96	0.291

$^{*}p < 0.05$; $^{**}p < 0.01$.

4.5.2. Model for the Combined Data. Table 5 shows the multiple regression output. The results showed that *ROAE* (β = 0.15, $p = 0.02$) and *AUTREG* (β = 0.25, $p = 0.01$) were the two predictor variables that had statistically significant effects on performance, apart from *GPA*, *number of work hours/week*, and *class format*. Specifically, students with higher degrees of autonomous motivation and students who engaged more in reflective observation and active experimentation in their learning performed significantly better in this course, regardless of format. Students in the online sections had significantly poorer performance in the course than traditional students (β = −0.19, $p = 0.03$), replicating prior studies (Nelson 2006, Paden 2006, Wilson and Allen 2014). Among the goal-orientation variables, *LGO* (β = 0.31, $p = 0.001$) and *PGO* (β = 0.26, $p = 0.02$) had statistically significant effects on performance. Moreover, *INTRVAL* had a significant effect on performance (β = −0.26, $p = 0.03$). Students with stronger approach goal orientations and greater degrees of intrinsic value performed significantly better. This is consistent with expectations because all of these factors are related to the students' inherent interest in improving their competencies as well as performance in the course, thus leading to greater effort and hence better grades at the end. *GPA* had a positive association with performance (β = 0.27, $p = 0.001$), as expected, whereas *number of work hours* had a negative association (β = −0.29, $p < 0.0001$), implying that students working longer outside of school experienced impaired performance.

Considering the proportion of overall variance explained by the different variables in the model, the R^2 changes showed that class type explained 19% of the variance in performance, the significant predictors explained 35.5%, and the remaining 23.1% was accounted for by the other predictors and the control variables (overall R^2 for the model: 0.766). This further established the importance of the significant cognitive factors (*AUTREG*, *ROAE*, *INTRVAL*, *LGO*, and *PGO*) in determining student success for our bottleneck business course.

Table 5. Multiple Regression Model Output for Student Performance with All the Data

Variable	B	Standard error for B	β	p
Gender	−0.13	0.14	−0.07	0.43
Age: 25–34[a]	0.01	0.12	0.01	0.94
Age: 35–44[a]	0.03	0.13	0.01	0.92
Age: 45 and older[a]	0.02	0.14	0.01	0.92
Ethnicity: Hispanic[b]	0.64	0.34	0.15	0.08
Ethnicity: Asian/Pacific Islander[b]	1.09	0.24	0.26	0.22
Ethnicity: African America[b]	0.28	0.36	0.06	0.51
First-generational status	0.87	0.48	0.15	0.16
Transfer status	−0.02	0.08	−0.05	0.71
GPA	0.61	0.17	0.27	0.001**
Number of work hours/week	−0.02	0.004	−0.29	<0.0001*
ROAE	0.24	0.19	0.15	0.02*
AC	−0.23	0.11	−0.15	0.10
CE	−0.19	0.18	−0.12	0.36
AUTREG	0.31	0.11	0.25	0.01*
CONREG	−0.42	0.12	−0.27	0.001**
LGO	0.25	0.07	0.31	0.001**
LAGO	−0.003	0.05	−0.004	0.96
PGO	0.18	0.17	0.26	0.02*
PAGO	−0.04	0.05	−0.07	0.63
SLFREG	0.004	0.05	0.04	0.19
INTRVAL	−0.43	0.14	−0.26	0.03*
PROC	−0.021	0.01	−0.02	0.56
Class type (0 = f2f; 1 = OL)	−0.379	0.17	−0.19	0.027*

Notes. f2f, face-to-face; OL, online learning. $R^2 = 0.776$; adjusted $R^2 = 0.759$. Model ANOVA $p < 0.0001$ (significant at 5% level), $n = 140$.
[a]18–24 age category used as baseline.
[b]White category used as baseline for ethnicity.
*$p < 0.05$; **$p < 0.01$. The p values < 0.0001 were obtained as "0" in the SPSS output.

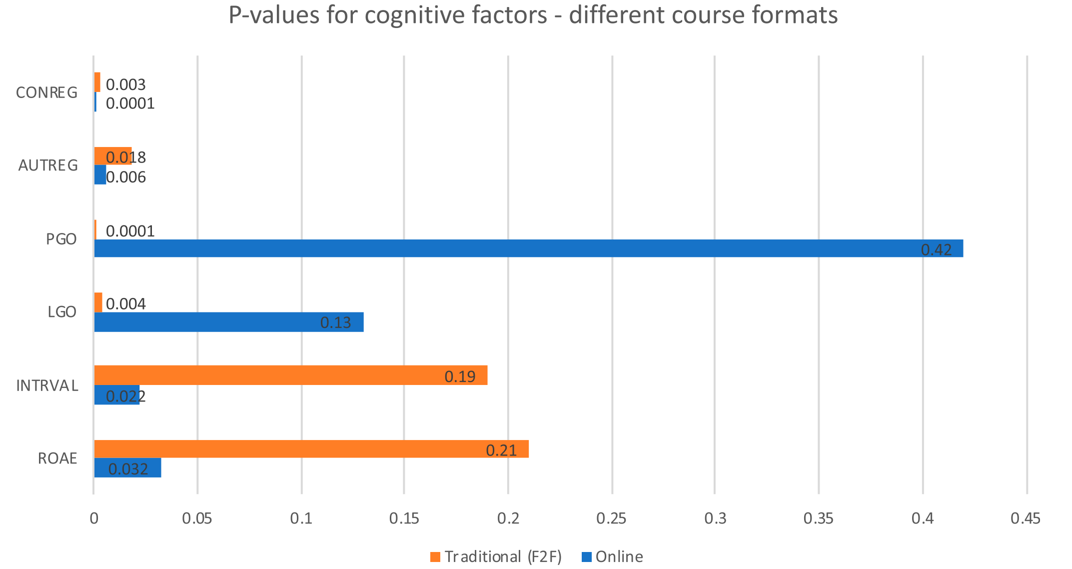
4.5.3. Comparing Traditional and Online Sections in Terms of Differences in Associations. Two distinct multiple regression models for traditional and online course sections showed that the effect of the motivational factors on student performance indeed varied across class formats ($n = 93$ for traditional sections and $n = 47$ for online sections). Figure 1 highlights the primary differences observed between the two models.[2] For online students only, *ROAE* learning style ($p = 0.03$) and intrinsic value ($p = 0.022$) were positively associated with performance. For traditional students only, learning and performance approach goal orientations were positively associated with performance ($p = 0.004$ and $p < 0.0001$, respectively). For both online and traditional students, the variables representing both autonomous (intrinsic) and controlled (extrinsic) motivational styles ($p = 0.018$ and 0.006 for *AUTREG* for traditional and online classes, respectively; p's = 0.003 and 0.0001 for *CONREG* for traditional and online classes, respectively) were positively associated with performance, the same as in the model for the combined data.

4.6. Factors Affecting Course Format Enrollment

For the logistic regression model, the dependent variable was the class type in which students enrolled (0 = face-to-face; 1 = online) with the same controls and predictors as the previous models. The Hosmer–Lemeshow goodness of fit test (Hosmer and Lemeshow 2000) for our model yielded a p-value of 0.10, indicating that the model was adequate. Moreover, the omnibus test of the model coefficients yielded a p-value equal to 0.01, indicating that the predictors explained significant variation in the data.

Table 6 shows the results from the logistic regression model predicting class enrollment. For logistic

Figure 1. Comparing the Effects of the Various Cognitive Factors for Traditional (Face-to-Face) Sections and Online Sections of the Business Course



regression, the Wald statistic is used to test for the significance of each coefficient, and its chi-square distribution has one degree of freedom (Hosmer and Lemeshow 2000). The significant motivational factors included *AUTREG*, *LGO*, and INTRVAL (p's = 0.003, 0.015, and 0.021, respectively). Specifically, (i) students with higher levels of autonomous motivation and higher intrinsic value were more likely to enroll in an online course section, whereas (ii) students with higher values of *LGO* were more likely to enroll

Table 6. Logistic Regression Model for Student Self-Selection of Class Format

Variable	B	Standard error for B	Wald	p	Exp(B)
Gender	–0.52	0.52	1.01	0.32	0.60
Age: 25–34	0.04	0.04	1.19	0.27	1.04
Age: 35–44[a]	0.03	0.08	0.55	0.46	1.03
Age: 45 and older[a]	0.02	0.07	0.58	0.45	1.02
Ethnicity: Hispanic[b]	0.15	0.08	1.22	0.27	1.16
Ethnicity: Asian/Pacific Islander[b]	0.19	0.09	1.88	0.17	1.21
Ethnicity: African American[b]	0.18	0.11	1.07	0.30	1.20
First-generational status	–0.91	0.53	2.99	0.08	0.40
Transfer status	0.18	0.27	0.45	0.50	1.20
GPA	–0.31	0.63	0.24	0.62	0.73
Number of work hours/week	0.03	0.02	4.51	0.03*	1.03
ROAE	0.42	0.74	0.32	0.57	1.52
AC	–0.91	0.53	2.96	0.08	0.40
CE	0.73	0.72	1.06	0.30	2.09
AUTREG	1.07	0.29	4.56	0.03*	2.91
CONREG	0.71	0.50	2.03	0.15	2.03
LGO	–1.14	0.56	4.10	0.04*	0.32
LAGO	0.28	0.23	1.50	0.22	1.33
PGO	–0.26	0.26	1.00	0.32	0.77
PAGO	–0.01	0.23	0.002	0.97	0.99
SLFREG	0.33	0.57	0.32	0.57	1.52
INTRVAL	1.19	0.24	5.12	0.025*	3.29
PROC	0.12	0.30	0.16	0.69	0.34

Notes. Exp(B) denotes the odds ratio. Cox & Snell $R^2 = 0.351$. Omnibus test of model coefficients has a p-value of 0.010 (significant at 5% level); n = 140. Wald represents the chi-square test statistics used for testing the coefficients in the model.
[a]18–24 age category used as baseline.
[b]White category used as baseline for ethnicity.
$*p < 0.05$.

in a face-to-face section. According to the odds ratios obtained from the model, a student with one unit higher autonomous motivation was 2.9 times more likely to enroll in an online class section than a traditional section; a student with one unit higher intrinsic value was 3.3 times more likely to enroll in an online section than in a traditional one; and, finally, a student with one unit higher learning goal orientation value was 3.12 times more likely to enroll in a traditional section compared with an online section of the course. For the controls, students working one additional hour outside of school were 1.03 times more likely to enroll in an online class ($p = 0.03$). This is consistent with expectations because such students tend to look for flexible schedules to accommodate their work. Lastly, it is often believed that low-performing students prefer online courses, as these are perceived to require less effort. Our results, however, showed that *GPA* was not associated with course selection.

5. Discussion and Conclusions

Our results provide an initial, yet critical, understanding of factors associated with student performance and enrollment in different instructional modes of a business statistics course. This study provided comprehensive insights into the impact of a variety of intrinsic factors associated with student performance and selection of an online versus traditional format in a bottleneck course; hence, its impact is even more significant, as strategies to improve completion rates in such courses are extremely critical. The overall pattern of results indicated that students who enrolled in an online class tended to have a stronger *ROAE* learning style, stronger autonomous or controlled motivational orientations, and higher intrinsic value compared with those who enrolled in a traditional class. In contrast, those in a traditional class tended to have stronger learning or performance approach goal orientations and higher grades compared with those in an online class. Furthermore, *ROAE*, learning and performance approach goal orientations, and autonomous motivational style all were positively associated with class performance, whereas controlled motivational style, intrinsic value, and enrollment in an online course were all negatively associated with performance. Finally, consistent with these prior findings, students who were more autonomously motivated with higher intrinsic value were more likely to enroll in an online course, whereas those with a stronger learning-approach goal orientation were more likely to enroll in a traditional course. Overall, this pattern of results suggests that students who are more autonomous, intrinsically motivated, and self-directed in their motivational style are more likely to enroll in an online bottleneck business statistics course given the chance. The fact that students who worked more hours also were more likely to select an online course further reinforces the greater autonomy afforded to those students. This is consistent with the less structured nature of online courses and the greater autonomy that such courses offer students. The stronger association of a *ROAE* learning style (more focused on watching/doing versus feeling/thinking) also suggests that students in online courses may be more "hands on" in their learning, and less apt to prefer a lecture-focused approach to instruction for a business statistics course.

A few results regarding controlled (extrinsic) motivational style and intrinsic value being negatively associated with performance, yet significantly higher for online enrollees, are worth reflection. First, controlled self-regulation is expected to be associated with less persistence, lower achievement, and, consequently, lower grades (Deci et al. 1991). It is no surprise, therefore, to find that controlled motivational orientation was negatively associated with performance. Why those online class enrollees had higher scores on this variable is less clear. One possibility is that some students felt more externally compelled to take an online course due to pressures from school, outside work, or other stress-oriented factors. Another possibility is that some students had mixed motivations in taking online courses, as suggested by the moderate correlation (0.34) between intrinsic value and controlled motivational orientation. Future research may consider further exploring differences in controlled regulation for online and traditional courses. In any case, it is important to note that only autonomous motivation and intrinsic interest predicted selection of an online (versus traditional) course, consistent with the greater autonomy students experience in such courses. Second, the fact that intrinsic value was negatively associated with performance is not surprising; it is consistent with the notion that intrinsic interest can motivate students to focus more on learning content that they find personally interesting than grades. Future research may consider whether a negative relationship between intrinsic value and performance is sufficiently strong to impair a student's successful completion of a course or whether it merely means the difference between a higher or lower passing grade.

Finally, both learning and performance approach goal orientations were stronger in conventional versus online courses, and learning orientation was positively associated with selection of a conventional course. The positive association of approach-oriented motivation (both learning and performance) with academic performance is consistent with prior research (Meece et al. 2006). The fact that students who were more learning oriented were more likely to select a conventional course suggests a potential student perception that online courses offer less opportunities for learning than face-to-face instruction. This would be in contrast to the perception that online courses offer greater autonomy and potential to pursue learning at one's own pace and in a more self-directed manner. Further research should investigate whether students who are learning-oriented in some settings may view online classes as less rigorous or providing less opportunity for learning than traditional classes.

The growth of online education continues today at a very rapid pace. More and more institutions of higher education are developing online courses and degree programs, which provide working students the flexibility they require to attend college. More importantly, the emergence of fully online MOOCs (like Coursera and edX) and other online offerings and certifications from companies like Microsoft are creating tough competition for colleges and universities, which have no alternative but to develop online curricula, as students are increasingly choosing to enroll in those. Hence, such a study is very timely and relevant because it is imperative to understand what types of students are expected to select and succeed in online courses and programs, especially bottleneck statistics courses that are associated with high failure rates and act as barriers to timely graduation. This study thus has broad practical and theoretical significance in both traditional and online education. Practically, as suggested by many researchers in online educational and training programs (e.g., Tucker 2001 and Valenta et al. 2001), different learning-style inventories can be used to adapt instructional strategies to learner needs, to design alternative curricula, to help individuals select courses or work environments compatible with their learning styles, and to help reduce dropout rates. Similarly, goal orientations and motivational factors play an important role in learning; hence, insights about those are also useful in suitably redesigning courses that may help enhance motivation and help them modify their goals in terms of learning and performance. Although in recent years, most studies of this kind have focused on online learning, we must remember that such studies also have the potential to benefit traditional students. This study provides one other potential way forward by pointing out that some student motivational profiles may thrive in an online environment. This could free up resources to focus more on traditional instruction for students who would be more vulnerable to failing the course. The findings from this study thus support all these perspectives, and they will continue to contribute to the existing literature related to learning styles and other cognitive factors and their impact on course performance, for both traditional and online courses.

The model for self-selection into a particular course environment also adds a novel perspective to this work by taking into account a set of diverse academic, demographic, and cognitive factors. The results from this model complemented those from the performance models. Just as autonomous motivation and intrinsic value proved to play a key role in students' decision to choose an online class over a face-to-face one, these two factors were also found to significantly affect student performance in those courses. Similarly, goal orientations were critical in both students' choice of a traditional face-to-face class as well as their performance in it. These results offer important implications for improved and targeted student advising, course design, and delivery that can be appropriately tailored to meet student needs in both face-to-face and online classes. For instance, although students who work more outside of school may be more inclined to enroll in an online course, this may also put them at a risk for lower performance in the course. It is also important to consider whether students with stronger approach motivation (either learning or performance) have biases that online business statistics courses may be less challenging academically or offer less opportunity for learning. Those students are thus less likely to enroll in online classes. So program managers and administrators can consider introducing programs and resources to educate students about the structure of an online class environment and share some tips and advice regarding how to succeed in it (e.g., more self-regulated, motivation, and time-management skills). This will help students make an informed decision about which course format to enroll in, so that flexibility is not the only criterion driving their choice. Moreover, ongoing support programs to provide additional help to online students are also important to ensure their success as online instruction becomes more and more popular. Such a study can easily be replicated for courses in other disciplines and can henceforth go a long way in impacting student success efforts at educational institutions worldwide.

Because our study focused on a business statistics course, the findings are particularly relevant to faculty teaching any analytical and quantitative business courses in the areas of management science (MS), operations research (OR), and business analytics (BA) that require computational, problem-solving, and critical-thinking skills. In many cases, statistics is a pre-requisite course for higher-level MS/OR/BA courses and provides the mathematical foundation for more advanced topics in those fields. Consequently, the insights obtained from our analyses are applicable to those, too, because of their similar nature and often similar difficulty levels that may make them bottleneck as well. In fact, these findings from a business statistics course can prepare instructors teaching MS/OR courses with knowledge about the intrinsic nature of students enrolled in those courses, both in face-to-face and online formats, so that suitable changes may be effected, if needed, to boost success.

5.1. Limitations of the Study

This study had certain limitations. The data were collected from students, and hence there are always concerns about errors arising from self-reporting of certain variables like GPA, work hours, etc. Although a single course was used for the study taught by the same instructor, some of the conclusions may only be applicable to business statistics courses without the advantage of uniform generalizability to other courses in other disciplines. For the latter, a more large-scale study involving several courses should be conducted. Although the same study design can be replicated for any course or any set of courses (with the same variables), the results obtained might be different, and so will the conclusions and implications. Finally, although the study included several variables, both study and control ones, some other variables could also be included potentially; for instance, students' personality traits, which we will consider in our future work described below.

5.2. Conclusions and Future Work

This paper provided useful insights about learning styles and motivational factors that play a role in student performance in traditional and online sections of a bottleneck business statistics course. Furthermore, we identified factors that determine how students self-select to enroll in a certain course format, either traditional or online. We expect these findings to help higher-education administrators understand how to optimize resources among traditional and online sections of a bottleneck course (that struggles with high failure rates) in order to maximize student success, thus ensuring that students graduate on time.

As a preliminary study, this project lays the foundation for more in-depth analyses of the effect of the different factors that constitute our future work. Particularly, we wish to explore potential mediating and/or moderating effects of certain cognitive variables on course performance and on the decision to self-enroll in an online course Another potential direction is to study the effect of students' personality on their decision to self-enroll in an online course. Personality traits have been found to impact both career choices and academic performance (Hazrati-Viari et al. 2012), so this could add a potentially interesting and new dimension to our research endeavors. Lastly, causal relationships among the different variables with course performance can be explored with the help of structural equation models (Raykov and Marcoulides 2006).

Endnotes

[1] See http://courseredesign.csuprojects.org/wp/high-enrollment-low-success-courses-in-the-csu/.

[2] Detailed regression model outputs (available from the authors) are not displayed here due to space constraints.

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