

ABSTRACT

HALL, MARK MONROE. The Impact of Proactive Student-Success Coaching Using Predictive Analytics on Community College Students. (Under the direction of Dr. Stephen Porter).

The purpose of this study was to examine the effects of proactive student-success coaching, informed by predictive analytics, on student academic performance and persistence. Specifically, semester GPA and semester-to-semester student persistence were the investigated outcomes. Uniquely, the community college focused the intervention on only students predicted to be moderate-level academic performers instead of to all students or to students predicted to be low-level performers. Few studies have investigated interventions like student-success coaching, and no research has addressed student-success coaching restricted to students with a particular predicted academic performance.

This study used inverse probability of treatment weighting to create appropriately balanced samples of the proactively coached students and not proactively coached students in order to approximate a randomized control trial with observational data. Regression analyses with weights and covariates estimated few statistically significant results in sample subgroup models and no statistically significant results for whole-samples. Generally, the results found in this study do not support the hypothesis that proactive student-success coaching initiated by the predictive analytics of a student-monitoring system improves student outcomes. Nonetheless, this study contributes empirical results to the emerging literature regarding student-success coaching, predictive analytics, and student-monitoring systems (also known as Integrated Planning and Advising for Student Success or early-alert systems).

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The Impact of Proactive Student-Success Coaching Using Predictive Analytics on
Community College Students.

by
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DEDICATION

To my wife, to my children, and to my parents, thank you for the support and patience.

&

To all of the students who earned a C in undergraduate statistics.

BIOGRAPHY

As a native and lifelong resident (so far) of North Carolina, Mark Hall has lived in several cities and towns across the Old North State. He completed his Bachelor of Arts in Psychology at Appalachian State University, where he also worked as a behavioral neuroscience research assistant. Following a few years and a few different career paths, he returned to higher education and earned a Master of Arts in English and American Literature from North Carolina State University. After teaching English and humanities courses for almost a decade in settings ranging from high schools to prisons to community-college campuses and after assuming various leadership roles, he decided to pursue a Doctor of Philosophy in Educational Research and Policy Analysis with a specialization in Higher Education Administration at North Carolina State University. While a doctoral student, he entered full-time academic administration as a provost for Central Carolina Community College.

Upon graduation, he plans on continuing to research emerging innovations in higher education and hopes to be found playing guitar with his family and kayaking with Team Flatwater.

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CHAPTER 1: INTRODUCTION

Student retention is a challenge for postsecondary education institutions. More than four-year institutions, community colleges struggle to retain students. From the fall of 2012 to the fall of 2013, four-year institutions retained about 80% of their first-time college students, but community colleges only retained 60% (Kena, Musu-Gillette, Robinson, Wang, Rathbun, Wilkinson-Flicker, Barner, & Velez, 2015). Of the retained community college students who started in the fall of 2012, only about 30% of them were likely to persist to graduation within three years (Kena et al., 2015). The congruent goals of improving institutions' retention of students and supporting students' persistence to graduation have produced ongoing research and innovative interventions.

Particular to this study, some educational institutions have started using analytics to predict student academic behaviors and outcomes. These institutions use the predictions to inform and offer proactive interventions to students if needed (Campbell, DeBlois, & Oblinger, 2007; Clow, 2013; Jayaprakash, Moody, Lauria, Regan, & Baron, 2014; Phillips, & Horowitz, 2013; and Smith, Lange, & Huston, 2012). Although institutions have increasingly employed predictive analytics to improve student success, the literature concerning analytics predominantly addresses the data mining methods and the software used to build the predictive models utilized by various organizations and institutions (Agudo-Peregrina, Iglesias-Pradas, Conde-Gonzalez, and Hernandez-Garcia, 2014; Campbell et al., 2007; Denley, 2014; Picciano, 2012; and Siemens, 2013). Generally, the literature lacks examples of research that has relied on experimental or quasi-experimental methods to

estimate the effects of providing predictive-analytics-informed proactive interventions to students. This study did.

The use of analytics to anticipate individuals' behaviors is more ubiquitous than many might realize (O'Neil, 2016; and Siegel, 2013). Many different types of organizations and institutions use analytics to predict the likely actions and choices of any particular service-users. These predictions are based on the data collected about specific individual users and on how that data compares to others like them. Google and Amazon are two commercial examples of organizations that use predictive analytics as their recommendation mechanisms. These companies constantly analyze user data—the clicks, searches, purchases, locations, and visited websites of their users—to recommend products and services users are estimated most likely to purchase based on their own historical data and on the data of other users similar to them.

In educational settings, analytics have been used for almost twenty years to develop predictive modeling for administrative functions like enrollment management (Campbell et al., 2007). When considering which applicants to accept, some institutions would estimate the likelihood of their applicants to have successful educational outcomes, such as persistence to graduation, based on models developed from estimates of the likelihood of their previous students to have successful outcomes. These estimations were mostly derived from preadmission demographic and academic preparation data correlated with outcomes. With the widespread use of learning management systems and student-monitoring and alert systems, institutions have been able to collect, store, and analyze much more student data

than they could twenty years ago. More importantly, these systems can collect data about students' actions (e.g., course attendance and course-site login frequency) and students' outcomes (e.g., up-to-date course grades and cumulative GPA). Combined with student-records data, some institutions have used learning management systems' historical student data to develop algorithmic models that estimate previous students' odds for successful academic outcomes. The models are then applied to current student data to estimate the odds of current students having successful academic outcomes. In short, institutions utilizing analytics are able to make predictions about student outcomes and to use those predictions to identify students' potential obstacles for success and to offer support to students as needed and as indicated.

While retention and persistence have been thoroughly studied issues in education (Astin, 1993, 1999; Bean, 1980; Karp, Hughes, & O'Gara, 2010; Pascarella, & Terenzini, 2005; and Tinto, 1975, 1993, 2006), few researchers have analyzed the efficacy of exploiting analytics to predict student outcomes and to offer individualized and coordinated interventions to improve those student outcomes. Research that adequately addresses selection bias and/or uses quasi-experimental or experimental methods has not yet been conducted, save for Bettinger and Baker (2014). In this study, I examined the effects of a proactive student-success-coaching intervention at a southeastern community college. The proactive student-success-coaching was offered to students for whom the predictive analytics of a student-monitoring and alert system estimated would likely achieve moderate academic outcomes in their courses—earned grades of low Bs or Cs. The findings of this study

contribute to the broad literature about retention and to the developing literature about the use of analytics to offer proactive targeted and customized interventions in postsecondary education.

Background

Much has been written about retention and persistence in higher education (Astin, 1993, 1999; Bean, 1980; Karp, Hughes, & O’Gara, 2010; Pascarella, & Terenzini, 2005; and Tinto, 1975, 1993, 2006). This study expanded on the literature by addressing retention as it relates to student-monitoring and alert systems, predictive analytics, and proactive student-success coaching. Currently, the literature contains little rigorous research on these three areas and no research on the synthesis of these retention tools and practices.

Student-Monitoring and Alert Systems

Many institutions use various forms of information technology systems to maintain records for their students and monitor their current-semester performance. Systems that monitor students’ academic behaviors and outcomes during a semester are most often referred to as early-alert or early-warning systems. The majority of these systems notify the appropriate student-success stakeholders—students, faculty, advisors, and other student-support staff, like student-success coaches—after particular student-success indicators reach or surpass certain preset limits. For example, if students' reported midterm grades fall below a C average (numerical grades less than 70 for most institutions), the student-monitoring systems generate alerts that notify stakeholders that the midterm grade is low. The alert notification is meant to prompt stakeholders to react. Based on the type of the alert,

institutions can provide the appropriate interventions, such as tutoring services for the course in which the low midterm grade was reported. Since these alerts are sent only after an issue arises, the alerts are reactive responses rather than proactive actions. In most cases, the alert-generated intervention serves to prevent a student's academic performance from further deterioration. Following the above example, tutoring could help the student earn a better grade in the course, but being tutored after earning a low midterm grade seems to involve averting potential course failure more than achieving course expertise. In this way, most student-monitoring systems are not really early-alert systems but reactive-response systems that mitigate academic problems rather than prevent them.

Although there are numerous vendors for student-monitoring and alert systems, like AdvisorTrac, AvisoCoaching, Copley Retention, DropGuard, and Starfish Early Alert System (National Academic Advising Association, 2014), little empirical research exists about these systems. Many publications associated with discussions of these systems concern responses to alerts. Especially common are discussions about reacting to reported low midterm grades or absenteeism (Bruce, Bridgeland, Fox, & Balfanz, 2011; Faulconer, Giessler, Majewski, & Trifilo, 2014; and Johnson, 2001). Other reports simply review the implementation of early-alert systems (Hanover Research, 2014; and O'Cummings & Therriault, 2015). Furthermore, searching for studies on early-alert systems yields divergent concepts of such systems, ranging from orientation surveys that could be used to identify at-risk students (Beck & Davidson, 2001) to sophisticated software programs that collect student-level data from learning management and institutional record systems that alert

students, advisors, and faculty about issues correlated with student dropout or poor course performance (Agudo-Peregrina et al., 2014; Bettinger & Baker, 2014; Bruce, Bridgeland, Fox, & Balfanz, 2011; and Pistlli & Arnold, 2010).

This study investigated the latter type of inter-networked student-monitoring and alert systems. The community college in this study used AvisoCoaching (so named during the time period from which this study's data came; now named AvisoRetention). Distinctive to this system was its incorporation of predictive analytics into its student-monitoring platform starting in the fall 2015. Using predictive analytics, the system developed algorithmic models from the college's historical student data and then applied those models to current student data to predict the current students' academic performances in each of the courses in which they were enrolled. Proactively, student-success coaches used these estimations to offer interventions to students within the first few weeks of the fall semester; that is, academic assistance was offered to students before predicted academic outcomes occurred. Explained in more detail in Chapter 3, these predicted performances were based on success measures (variables within the data) that allowed student-success coaches to provide individualized interventions that were proactive instead of reactive. Whereas most student-monitoring systems are actually reactive-response systems, the system the community college used was designed to help coaches preempt and prevent potential academic issues. Continuing with the above example about low midterm grade alerts, student-success coaches using predictive alerts would attempt to arrange a tutor for a course in which a student was predicted to earn a

low grade weeks before the student had the chance to earn a low midterm grade. The use of predictive analytics provided the coaches the opportunity to support students proactively.

Analytics

Not unlike the literature about student-monitoring and alert systems, the literature on analytics in education has yet to coalesce around what is meant by analytics. In fact, for several years researchers of analytics have refined their definitions and established sub-categories for analytics (bin Mat, Buniyamin, Arsad, & Kassim, 2013; Clow, 2013; Macfadyen & Dawson, 2012; Picciano, 2012; and Siemens, 2013;). This literature begins with the use of quantitative metrics—that is, “Big Data: the quantity, range and scale of data that can be and is gathered” (Clow, 2013, p. 2)—especially after these metrics became much more feasible and prevalent with improvements in computing technology. Simply stated, analytics is the application of statistical analysis and algorithm models to big data to reveal patterns that can be used to estimate the likelihood of future outcomes. In education, these analytics have mostly been referred to as learning analytics.

Related to discussions of learning analytics are academic analytics, educational data mining, predictive analytics, action analytics, and data-driven decision-making (Agudo-Peregrina et al., 2014). Most scholars consider predictive analytics in education to be a sub-type of learning analytics. As the name indicates, predictive analytics are used to build statistical models that can predict, or rather estimate the likelihood of, student outcomes based on previous student data. Institutions can use these predictions to inform and offer proactive interventions that might improve student success beyond the predicted outcomes

(Campbell et al., 2007; Clow, 2013; Bettinger & Baker, 2014; Picciano, 2012; and Siemens, 2013). However, the literature on analytics lacks studies that examine the implementation of interventions based on predicted outcomes.

Student-success coaching

Despite the proliferation of student-success centers staffed with student-success coaches (or similar positions with various names at those centers), empirical research concerning this kind of intervention is relatively scarce. In fact, at the time of this study searching “student success coach” and “student success center” through Google yielded over 500 thousand results, most of which were for institutional centers or advertised open success-coach positions at those centers. However, searching the same phrases through Google Scholar produced only a little more than 700 results, only 40 of which included the exact phrase “student success coach” and almost all of which were corporate or non-profit organizational marketing reports instead of scholarly research. A search through the academic databases at a level-one research university returned even fewer results. Yet, some of the literature about retention and persistence implied that providing several coordinated interventions to students, which is what student-success coaching does, should increase student engagement and integration into an educational institution (Astin, 1999; Dadgar, Nodine, Bracco, & Venezia, 2014; Karp, Hughes, & O’Gara, 2010; Tripp, 2008; and Wild, & Ebbers, 2002). As a comprehensive intervention, student-success coaching blends student-support services and instruction as Dadgar et al. (2014) suggested; becomes the catalyst for students’ institutional information network that Karp et al. (2010) and Kuh (2007a) proposed;

and provides the one-on-one support for which Astin (1999), Tripp (2008), and Wild and Ebber (2002) advocated.

In brief, most student-success coaching involves actively contacting students about potential challenges to academic success and coordinating the support services for them that might help them overcome those challenges. Success coaches also advise students in typical and essential factors of persistence: time management, study skills, financial aid, extracurricular activities, faculty interaction, and intuitional knowledge. Furthermore, contacted students are typically students identified by an institutional process or student-monitoring and alert system for the intervention (Bettinger & Baker, 2014; Richie and Hargrove, 2004; and Tripp, 2008).

Intervention in Question

Few programs resemble the proactive student-success coaching intervention that the community college in this study implemented. According to Bettinger and Baker's (2014) descriptions, InsideTrack provided coaching services that were the most similar to AvisoCoaching. However, unlike InsideTrack, AvisoCoaching did not provide the student-success coaching to students. Instead, for the community college in this study, AvisoCoaching trained the college's faculty, student-support staff, and student-success coaches to use its online student-monitoring and advising platform, known to college employees simply as Aviso (heretofore also only referred to as Aviso). Until the start of the academic year in fall 2015, Aviso did not provide predictive analytics within its platform for the college. Previously, and like most other student-monitoring and alert systems, the system

generated reactive alerts about student success indicators that had already surpassed preset thresholds, like too many absences or current course averages below 70. These alerts typically started to occur about mid-semester and, thus, were not proactive. To generate these alerts, Aviso collected enrollment and attendance information from the college's institutional records and pulled current grades and login information from the college's learning management system, in which every course section at the college was required to have a course site for instructors to maintain up-to-date grades and provide course content.

Collecting all of the aggregated data accumulated over the several semesters the college had previously used the system, Aviso's analytics team constructed and applied predictive algorithms to every student enrolled in curriculum programs. For each course in which a student was enrolled, Aviso predicted how successful each student was likely to be. Although successful course completion was defined as having a predicted numerical course average of 70/C or above, the system distinguished among three predicted course performance levels. Aviso and the college referred to these levels as high-risk (predicted grades of less than 70), moderate-risk (predicted grades between 70 and less than 86), and low-risk (predicted grades 86 and greater). Aviso and the college considered "risk" to be the potential that a student would achieve poor academic outcomes in a given course. For example, students predicted to earn less than 70 for a course were considered at "high-risk" for unsuccessful completion of that course and likely to earn either a D or an F for the course. Likewise, students considered at "moderate-risk" for unsuccessful course completion for a

particular course were predicted to earn a final grade of a low B or C for the course but not a grade of D or F.

Since the language of “risk” used by Aviso and the College was obfuscated and was not aligned with educational literature’s typical use and meaning of the phrase, this study substituted performance levels for Aviso’s “risk” levels. In the language of this study, estimated high-performance in a course denoted the student was predicted to earn either an A or high B in a given course; moderate-performance signified the student was predicted to earn a low B or C in the course; and, low-performance meant a student was predicted to earn either a D or an F in that course.

The course-level performance predictions were based on students’ background characteristics (e.g., age, gender, ethnicity, and socio-economic status) and academic preparation information (e.g., placement test scores and previously earned GPA). Grade predictions were made for each course in which a student was enrolled, which meant that students had a range of predicted grades across their course schedules. For example, a student could be predicted to be a high-performer in a literature course but also predicted to be a moderate-performer in a science course. In addition to course-level performance predictions, Aviso classified each enrolled student at the student-level as either a high-, moderate-, or low-performer. The student-level classification was based on students’ lowest predicted course grade. Discussed in more detail in Chapter 3, high-performing students had only high-performance course predictions; moderate-performing students had at least one moderate-performance prediction and no low-performance predictions; and low-performing students

had at least one low-performance prediction but could have moderate- or high-performance predictions too.

The Aviso platform did not allow student-users to see these predictions, but college personnel had access to students' predicted performances. Starting Fall 2015, the college's student-success coaches proactively contacted all students classified as moderate-performers to coordinate support services and to provide one-on-one support from the beginning to the end of the semester, before predicted academic issues could occur. For various reasons, the college offered targeted proactive student-success coaching to only moderate-performing students. Targeting the proactive student-success coaching intervention to students predicted to be moderate-performers merited determining whether or not the intervention did, in fact, have an effect on these students' outcomes that were significantly different than the outcomes of students otherwise classified. Furthermore, that research on this specific type of proactively targeted intervention is lacking in the literature warranted this study.

Student-success coaching at the community college selected for this study. The implementation of student-success coaching and similar practices differ among institutions. For example, as previously discussed, InsideTrack's coaches were not employees of the institutions in which the students were enrolled, and its coaches interacted with students through email and phone conversations since they were not located on the students' campuses. Student-success coaching at the community college selected for this study had similar goals, but the intervention was implemented by on-campus, college-employed coaches, who used the Aviso platform and its predictive analytics as tools to coach students.

At the selected college, the coaching process started after students were enrolled in courses and after Aviso's course-success predictions were generated at the start of the semester. Using students' Aviso student-level performance classifications, student-success coaches generated caseloads of moderate-performers, whom they started contacting within the first couple of weeks of the semester. The process of contacting students was proactive and, thus, intrusive in that the intervention relied on the assumption that students needed to be offered assistance before they realized they might need it and on the assumption that such students might not seek assistance or be knowledgeable about support services. The coaches were required to initiate contact with moderate-performing students instead of waiting for the students to initiate contact or for reactive alerts to be generated later in the semester.

Purpose of Study and Research Questions

Current literature on retention and on analytics lacks sufficient empirical research about the use of student-monitoring and alert systems, the use of predictive analytics in educational contexts, and the use of these tools in conjunction with each other. Very few studies specifically investigate student-success coaching (or its variants) as a way to improve student outcomes. In particular to this study, the literature has yet to examine the potential effects of coordinated and analytics-informed interventions offered to students estimated to be moderate-performers and, by extension, moderately at risk for premature departure from the college.

The purpose of this study was to examine the impact of offering proactive student-success coaching to students who were estimated to be moderate-performers by the college's

student-monitoring and alert system, Aviso, using predictive analytics. Since the college offered the intervention to all moderate-performing students, this study could not retroactively conduct a randomized controlled trial experiment to estimate the effects of the intervention. Fortunately, comprehensive data from Aviso were available for analysis in this study. With that data, this study used the inverse probability of treatment weighting method to create comparable groups of students offered and not offered student-success coaching. These groups were analyzed to ascertain the possible, if any, causal associations between the intervention and student outcomes, specifically students' fall semester GPAs and fall-to-spring persistence. The overarching questions that guided this study were:

1. For students predicted to be moderate-performers, what was the estimated effect of proactive coaching on academic performance, as measured by semester GPA?
2. For students predicted to be moderate-performers, what was the estimated effect of proactive coaching on fall-to-spring persistence?

CHAPTER 2: LITERATURE REVIEW

This study spanned several interrelated but diverse areas regarding student success in higher education: general retention practices, early-alert and predictive-alert student-success monitoring systems, learning and predictive analytics, and student-success coaching. Generally, the purpose of research in each of these areas is to ascertain and understand the dynamics involved in student success and/or failure, so that educational practices can be grounded in empirical knowledge and not conjecture. While the literature about retention is particularly extensive, the bodies of literature about student-monitoring systems, analytics, and student-success coaching are not. In fact, most of the material about student-monitoring systems is typically antidotal, as is the research on student-success coaching, and the majority of the research in the field of educational analytics is technical. Moreover, research in these areas is often conflated, blurring the distinctions among them. In light of these observations, the review of literature in the above areas discusses, in order, general retention practices, student-success monitoring systems, learning and predictive analytics, and student-success coaching.

General Retention Practices

Retention and persistence are different perspectives on the same process: students' continual enrollment until graduation. Whereas the study of student persistence focuses on the students' attitudes and behaviors as associated with their educational attainment, the study of retention focuses on institutions' environments and processes as associated with continued student enrollment through graduation (Astin, 1993, 1999; Boden, 2011; Cabrera

et al., 1992; Pascarella & Terenzini, 2005; and Tinto, 1975, 1993, 2006). A thorough review of educational attainment research can be found in Pascarella and Terenzini (2005), which consolidated much of what has been demonstrated about student and institutional variables associated with attainment and about the interventions designed to mitigate or enhance the impact of those variables on student persistence and institutional student retention.

In short, Pascarella and Terenzini (2005) found the literature to suggest that interventions addressing student issues with academic deficits, institutional bureaucratic barriers, and interactions with faculty and support staff modestly influence improvements in student outcomes. Such interventions include practices like remedial education, supplemental instruction, tutoring, first-year seminars, early-alert systems (a type of student-monitoring systems), advising and counseling programs, summer-bridge programs, academic-skill development programs and workshops, and experiential-learning courses and opportunities (Bettinger & Baker, 2014; Dadgar et al., 2014; Karp et al., 2010; Singell & Waddell, 2010; and Wild & Ebbers, 2002). The problems with estimating the effects of any of these practices are that control groups are difficult to establish for the required interventions. For example, remedial education is required for students whose placement test scores do not allow them to take higher level courses. Furthermore, selection bias is difficult to overcome when analyzing interventions in which students choose to participate. For example, enrollment in first-year seminars at most institutions is not required; therefore, students who choose to enroll in these courses are likely different in some way from students who choose not to enroll. Nonetheless, these types of interventions seem to be widely adopted, and

institutions seem to implement some form of programming for several, if not all, of these practices—confounding the empirical study of any one intervention.

Adding to the confounding effect of concurrently implementing several intervention programs, much of the research on retention interventions has relied on statistical analysis that does not adequately estimate the counterfactual outcomes as discussed by Khandker, Koolwal, and Samad (2010). Estimating the counterfactual of an intervention is best accomplished through randomized controlled trials but is also achievable through quasi-experimental methods such as propensity score matching and regression discontinuity. Using experimental or quasi-experimental methods provides stronger support that a particular intervention has a causal relationship with improved outcomes than research that does not account for the counterfactual.

For example, while the multivariate regression models in Fike and Fike's (2008) study of developmental education courses and retention attended to relevant predictor variables, the results were only correlational and cannot be interpreted as causal since no attempts were made to create comparable control groups within the data set. The same could be stated about Singell and Waddell's (2010) use of probit models in the discussion of identifying and retaining at-risk students; Beck and Davidson's (2010) analysis of orientation survey results used as an early-warning system for retention; and Svanum and Bigatti's (2009) investigation into course academic engagement as a predictor for downstream success outcomes like retention.

A few other studies, however, relied on more rigorous research designs than did the above examples. Bettinger and Baker (2014) conducted a randomized controlled trial to estimate the effects of student coaching on retention; Schnell and Doetkott (2002) used propensity score matching to evaluate the impact of first-year seminars on retention; and Munt and Merydith (2011) used the instrumental variable estimation to explore the connections among personality traits, psychological characteristics, and retention.

The latter set of the above studies resolved most concerns that might undermine causal claims that the former set of studies did not. More importantly, all of the above studies reinforced the significance of Tinto's (1975, 1993) institutional experiences and academic integration segments of his Longitudinal Model of Institutional Departure to retention. That is, as Tinto (1975) stated, "given individual characteristics, prior experiences, and commitments, the model argues that it is the individual's integration into the academic and social systems of the college that most directly relate to his continuance in that college" (p. 96). The strong support from the literature that academic integration is foundational to students' educational attainment seems to justify the use of tools, such as student-monitoring systems, to implement interventions demonstrated to be successful in the retention literature.

Student-success Monitoring Systems

Generally, the literature only refers to student-success monitoring systems as either early-alert or early-warning systems. Although surveys cited in a Hanover Research (2014) report indicated that over 90% of postsecondary institutions use "early-alert systems," it is unclear exactly what type of systems were being reported. For example, some applications of

these systems only occur within course sites of learning management systems (Agudo-Pergrina et al., 2014) and others consisted of reacting to survey data attached to student IDs (Beck & Davidson, 2001). However, the majority of systems involve the collection of student data from learning management systems and institutional records into the student-success monitoring systems to track student academic behaviors and performance and to provide possible reactive interventions (Bruce et al., 2011; Faulconer et al., 2014; Hudson, 2006; Jayaprakash, 2014; and O’Cummings & Therriault, 2015); that is, most student-success monitoring systems facilitate student-support interventions after issues have occurred. Even though clear distinctions are not found in the literature, this study differentiates between student-success monitoring systems that are reactive in design (early-alert systems) and those systems that are both reactive and proactive in design (predictive-alert systems).

The early-alert systems relevant to this study are the software platforms that monitor student-success indicators and notify students, faculty, and student-support staff when preset indicator limits are exceeded, such as alerts for low midterm grades. Students do not choose to participate in the alert portion of this intervention because institutions that adopt these types of reactive early-alert systems typically enroll their entire student population into the system. Any students who exhibit academic behaviors and/or performance that trigger alerts will be notified in some manner, such as emails for low course attendance (behavior) or low midterm grades (performance). Students, however, do make the choice to respond to the alert-notifications and to other forms of contact initiated by the systems. Essentially, while

early-alert systems include all students, alerted students must opt into any suggested intervention. The same is true for most predictive-alert systems: students must opt-in.

Unfortunately, and despite the reported widespread use of these systems, there is a dearth of research that uses rigorous study designs to estimate the impact of student-success monitoring systems on outcomes, and non-empirical survey results suggested the impact is inconsistent (Hanover Research, 2014). As examples, a study of the University of Maine's "Project 100: Early Alert/Early Intervention" program using mean comparisons and survey responses suggested that the intervention had little effect on retention and GPA (Johnson, 2000), but other studies suggested some positive correlations between alerts and student success using different systems: Purdue University's "Signals" (Campbell, 2007; and Pistilli & Arnold, 2010), an Early Alert and Referral System at a large public university in the southwest (Tampke, 2012), and Rio Salado Community College's combined S.T.A.R.S. and RioPACE programs (Smith et al., 2012). These studies were limited to chi-square tests and descriptive statistics comparisons. Clearly, more research is needed about the effectiveness of student-success monitoring systems on student outcomes.

Important to note is that a few of the recently developed student-success monitoring systems mentioned in the literature now utilize predictive modeling to identify students' probable course performances (Campbell et al., 2007; bin Mat, 2013; Pistilli & Arnold, 2010; and Smith et al., 2012). The interventions implemented by institutions operating these newer systems include proactively contacting students about potential challenges as well as generating and resolving reactive alerts (Campbell et al., 2007; Clow, 2013; O'Cummings &

Therriault, 2015; and Smith et al. 2012). While only about five percent of institutions surveyed by Educause presently use systems employing predictive analytics (Vendituoli, 2014), the research on analytics suggests numerous institutions currently using less sophisticated systems are likely to start using such systems in the near future (Arnold & Pistilli, 2012; bin Mat et al., 2013; Gasevic et al., 2015; O’Cummings & Therriault, 2015; and Vendituoli, 2014). In fact, a few recent articles and reports have documented how postsecondary institutions have lately used predictive analytics to encourage students to take certain actions associated with successful student outcomes before and during enrollment (Ideas42, 2016; Frankfort, Salim, Carmean, & Haynie, 2012; and Wildavsky, 2013).

Since the literature often combines discussions of early-alert and predictive-alert systems, noting the difference between the two types is important to this study. In short, early-alert student-success monitoring systems do not utilize predictive analytics and, thus, do not facilitate preemptive interventions at the start of a semester. Although the rhetoric about early-alert systems suggests that interventions are indeed early, they are not actually early in the semester. In fact, early-alert systems can only react to events that have already transpired. However, predictive-alert systems employ predictive analytics before semesters begin in addition to using all of the functions of typical early-alert systems during the semester. Table 2.1 presents a list of functions both types of systems use as well as the functions exclusive to predictive-alert systems.

Table 2.1
Student-success Monitoring Systems Differences

Functions	Early-alert	Predictive-alert
Course success predictions	No	Yes (pre-semester)
Retention success predictions	No	Yes (pre-semester)
Predicted success indicators	No	Yes (pre-semester)
Low-attendance alert	Yes (early-semester)	Yes (early-semester)
Infrequent login alert	Yes (early-semester)	Yes (early-semester)
Low current grade alert	No	Yes (early-semester)
Midterm grade alert	Yes	Yes
Final grade alert	Yes	Yes
Enrolled in unapproved courses alert	Yes (late-semester)	Yes (late-semester)
Caseload emails	Yes	Yes
Instructor-generated alerts	Yes	Yes
Administrative-generated alerts	Yes	Yes
Student-support staff generated alerts	Yes	Yes
Current semester schedule	Yes	Yes
Future semester suggested schedule	Yes	Yes

Note. The table is not a comprehensive list of student-success monitoring system functions; instead, the table provides a list of functions associated with using the systems as tools to prompt interventions with students. The parenthetical information regards the timing in which this function is first available. Early-semester is defined as within the first 4 weeks of the semester. These particular functions are used from the time indicated until the end of the semester.

While Table 2.1 does not provide all of the functions that most student-success monitoring systems might have, such as information sections on placement test scores and finances, it does list the functions related to implementing interventions with students. As the table indicates, the two types of systems are very similar; however, systems using predictive analytics enable institutions to offer support from the beginning of the semester through the end of the semester. Another important difference is that most predictive-alert systems

provide information about which student-level variables are estimated to influence a student's outcomes the most, and those variables are noted as predicted success indicators in the table. Combined with course-success and retention predictions, these success indicators provide student-support staff and faculty with actionable information upon which to personalize interventions. In essence, predictive analytics inform the possible preemptive and personalized interventions offered to students.

Learning and Predictive Analytics

Initially, the study of analytics developed out of advances in computer science and the exploration of the potential uses for innovations like data mining, social network analysis, user modeling, cognitive modeling, computer-based instruction, adaptive hypermedia, and online learning (Siemens, 2013). As an eclectic combination of several fields of study, analytics as a field unto itself has not yet been unified into a comprehensive discipline. In spite of still being in development, the definition of "learning analytics" most often cited in the literature (Arnold & Pistilli, 2012; bin Mat, 2013; Clow, 2013; and Haythornthwaite, de Laat, & Dawson, 2013) comes from one of the founders of the Society for Social Learning Analytics Research, George Siemens: "Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013).

Borrowing the business practice of using analytics on big data to understand the behavior and potential future actions of customers and markets, educational institutions

applied analytics to their own big data to make decisions about processes and efficiencies—a practice first known in education as educational data mining (Campbell et al., 2007; Jayaprakash et al., 2014; and Siemens, 2013). As institutions adopted the use of learning management systems, such as Blackboard and Moodle, some institutions began to apply analytics to the vast amount of data these systems can collect. This process was originally referred to as academic analytics (Campbell, 2007). The results of this application of analytics range from the personalization of computerized and online learning software programs to the development of user/student profiles and predictive modeling of student outcomes (Campbell, 2007; Campbell et al., 2007; Jayaprakash et al., 2014; and Siemens, 2013).

Typically considered a sub-type of learning analytics, predictive analytics in education involve the creation of the algorithmic models used to predict potential student outcomes in order to identify students who might benefit from proactive intervention. These predictions prompt and inform interventions with the students as needed (Agudo-Peregrina et al., 2014; Arnold & Pistilli, 2012; Campbell et al., 2007; Jayaprakash et al., 2014; and Siemens, 2013). While several institutions are noted for implementing programs using predictive analytics for areas like enrollment management, advising, career planning, and student-success monitoring systems, the example most cited is Purdue University's "Signals" system (Arnold & Pistilli, 2012; bin Mat et al., 2013; Campbell et al., 2007; Clow, 2013; and Jayaprakash et al., 2014). The Signals system predicts students' probability to pass each course in which they are enrolled with a grade of C or better. Despite different visual designs,

the online platform Aviso provided to the community college in this study greatly resembled that of Purdue University's Signals system: by using predictive analytics, both systems identified students based on the students' predicted performance in the courses in which they are enrolled. Each institution also provided interventions to students on the basis of how well they were predicted to perform. Interestingly, the effects of the interventions prompted by these systems on student outcomes have not been examined using either experimental or quasi-experimental research designs.

The research on the impact of the Signals system was correlational and mostly focused on the accuracy of the model predictions (Campbell et al., 2007). With enrollment, transcript, and learning-management-system data, Campbell (2007) developed the predictive model used in Purdue University's Signals system. Using correlational analysis, Campbell (2007) developed and tested several predictive models using a logistic regression model that estimated the odds of students successfully passing a course. In doing so, Campbell (2007) found that across the models academic preparation (standardized test scores), secondary and postsecondary GPA, learning-management-system use, and course level were variables consistently correlated with successful course completion. Student demographics were found to be more associated with predictions among students who used the learning management system less often than students who accessed those systems most often. Campbell's (2007) main model's prediction for course success (earned grade of C or better) was found to be 87.4% accurate compared to actual earned grades.

In fact, like Campbell's (2007) examination of the predictive precision of the model upon which the Signals system is based, the demonstration of model and method accuracy constitutes most of the current predictive analytics literature (Aguilar et al., 2014; Davis & Burgher, 2013; Delen, 2011; Denley, 2014; and Smith et al., 2012). For example, Aguilar et al. (2014) used five data analysis techniques (Naïve Bayes, decision trees, logistic regression, Hellinger distance decision trees, and random forests) to determine which approach provided the most accurate predictions of student retention within an engineering program at Notre Dame. They found that all of the approaches provided retention predictions with accuracies from 80% to 95% across subsets of a dataset (just academic variables or just engagement variables) as well as for the complete dataset. In addition to demographic variables, their dataset included academic preadmission factors, like standardized test scores, and postadmission indicators, like first semester GPA. The engagement variables included login frequency to the engineering learning management system and submission of work to that system. They found that using all of those variables yielded predictions that were 89% to 95% accurate across the different predictive methodologies.

Davis and Burgher (2013) found results similar to Aguilar et al. (2014) when they ran logit models on past enrollment and retention data. Independent variables such as high school GPA and non-first-generation higher education student status were shown to have odds ratios greater than one (5.130 and 1.545, respectively) indicating that these variables were correlated with increased fall-to-fall student retention, while variables such as late application submission and waiting a year between high school graduation and enrollment in higher

education were shown to have odds ratios less than one (.668 and .525, respectively) indicating that these variables were associated with increased student attrition (Davis & Burgher, 2013). Relying on such variables, Davis and Burgher (2013) developed and tested a predictive model for student retention and found that their model predicted retention along several subgroups within less than one percentage point from actual retention. Findings like these in the literature support the use and accuracy of similar variables in Aviso's predictive models.

Student-success Coaching

Collectively, the literature and theory about retention and persistence suggests that comprehensive intervention programming is needed to facilitate integration into the social and academic systems of postsecondary institutions and to remove the barriers to student success. Most institutions already have numerous interventions in which students could participate, but student-success coaching provides students with one point of contact to coordinate intentional interventions that might best serve the individual student. In the case of my study, predictive analytics informed the coaches' coordinated and individualized interventions. In practice, student-success coaches can bridge the divide between students and multiple support services, like writing centers and mental-health counseling (Tripp, 2008), and they can "help students to prepare academically for their courses, to counsel students on how to acquire better study skills, or to provide advice on how to identify additional academic resources at their respective institutions" (Bettinger & Baker, 2014, p. 5).

Almost no studies have been conducted on student-success coaching. Instead, research has investigated interventions ranging from the development of information networks and faculty interaction (Karp et al., 2010) and summer-bridge programs (Lonn et al., 2015) to telephone interventions for absenteeism and poor grades (Richie & Hargrove, 2004) and conditional contract student programs requiring regular advising meetings (Johnson, 2000). Collectively, the implications of this research suggest that some students require continual institutional support and contact to be successful. Additionally, most uses of student-success monitoring systems involve some advising and “coaching” of students regarding the various indicators (like low grades, poor class attendance, and infrequent learning management system logins) that triggered the system notifications and alerts (Arnold & Pistilli, 2012; Davis & Burgher, 2013; Hanover Research, 2014; O’Cummings & Therriault, 2015; and Smith et al., 2012). Important to note is that without student-success coaches, the support these systems initiate is not always consolidated and consistent. Instead, a changing mix of instructors and advisors might or might not act on system-generated alerts. Moreover, the alerts are signals from the system that an issue has already developed; the reactive alerts do not prompt proactive intervention that could change student behaviors prior to the development of academic problems. Student-success coaching coupled with predictive-alert student-success monitoring systems provides the opportunity to offer such preemptive intervention.

Although little rigorous research can be found about student-success coaching, Richie and Hargrove (2004) and Bettinger and Baker (2014) have examined very similar

interventions to the student-success coaching program of this study. Moreover, these two studies are the only ones that adequately addressed selection bias with experimental designs. As noted in earlier discussions, other research related to interventions similar to student-success coaching are at best correlational in design.

To examine the effect of a telephone intervention for excessive absences on student outcomes, Richie and Hargrove (2004) randomly assigned 25 entry-level English sections to an intervention or to a control group. As the treatment, eligible students in intervention sections were contacted about their absences and were advised about support services. The study's results indicated that after two semesters the telephone interactions and follow-ups increased average attendance by almost two days ($p < .01$), academic performance by 1 GPA point ($p < .01$), and fall-to-fall retention for students in the treatment group (77.5% retained compared to 62% retained in the control group) (Richie & Hargrove, 2004). While the telephone intervention did not constitute a comprehensive student-success coaching program and was not proactive in its implementation, this type of intervention is one of among many responsibilities of student-success coaches (Bettinger & Baker, 2014; and Tripp, 2008). Furthermore, Richie and Hargrove's (2004) study supports the claim that the offer of treatment can have a positive effect on outcomes even if students do not accept the treatment. Recent studies in behavioral science, especially related to medical interventions, corroborate the positive influence on the behaviors of individuals even if participation in the offered intervention does not occur (Castleman, & Page, 2016; Ideas42, 2016; Frankfort, Salim,

Carmean, & Haynie, 2012; Milkman, Beshears, Choi, Laibson, & Madrian, 2011; and Thaler, & Sunstein, 2008).

Bettinger and Baker's (2014) investigation of student-success coaching on retention found that students assigned to receive coaching and who accepted the treatment persisted at higher rates than students not assigned to the intervention. According to Bettinger and Baker (2014), the coaching company, InsideTrack, created "balanced groups" by randomly assigning 17 cohorts of students to balanced intervention and control groups for each institution using its service. InsideTrack then allowed the institutions to choose which of the two groups would receive coaching. Nonetheless, to affirm "the randomization" (p. 8), Bettinger and Baker (2014) took steps in their study to display that the groups were alike in their observable characteristics and "balanced" groups as needed. In addition to the methodological approach of Bettinger and Baker (2014), of interest to my study was InsideTrack's use of proactive and continual coaching as a treatment. The InsideTrack coaches not only mentored students assigned to the treatment before the occurrence of problems that might have negative impacts on academic performance, persistence, and retention, but the coaches also advised them through any problems that did arise.

The consistency of the coaching provided by InsideTrack that Bettinger and Baker (2014) examined distinguished the study from previous research. Additionally, the proactive approach to coaching also differentiated InsideTrack's intervention from the reactive practices of other institutions. Bettinger and Baker (2014) found statistically significant gains ($p < .01$) in retention that continued even after the coaching stopped. Specifically, Bettinger

and Baker (2014) found that “In contrast to the uncoached persistence rate of 58%, the retention rate among coached students was 63%” (p. 9). Their findings were relevant to my study because the coaching methods of InsideTrack and the proactive student-success coaching intervention under examination in the current study were similar, differing primarily in that InsideTrack employed its own coaches and Aviso trained coaches at the institutions with which it partnered. InsideTrack coaches “help students prepare academically for their courses, to counsel students on how to acquire better study skills, or to provide advice on how to identify additional academic resources at their respective institutions” (Bettinger & Baker, 2014, p. 5). The student-success coaches at the community college site in my study had the same responsibilities, but they were employees of the community college and were physically located at the community college’s service-area sites.

Synthesis and Application of the Literature

The motif of the above review is that while much research has been conducted on retention and its associated theoretical models, little research has been conducted on student-success monitoring systems, predictive analytics, and student-success coaching despite their proliferation at higher education institutions. Moreover, research has not been conducted on the synthesis of general retention practices, student-success monitoring systems, and predictive analytics into one channel of intervention: predictive-analytics-informed proactive student-success coaching. In my study, I examined proactive student-success coaching targeted at students Aviso predicted to be moderate-performers in their courses.

CHAPTER 3: AVISO SYSTEM AND STUDENT-SUCCESS COACHING

The Aviso system platform is a tool that student-success coaches use proactively to support students' academic integration and performance. The proactive use of information provided in the Aviso platform distinguishes it from other reactive-only early-alert student-monitoring systems. Most other student-monitoring systems alert appropriate institutional areas about issues, such as low mid-term grades, after they have already occurred. However, Aviso's predictive analytics allow student-success coaches to contact students before a predicted need arises in a particular course. While most early-alert student-monitoring systems notify institutions to prompt reactive support, the Aviso system provides student-success coaches the opportunity to initiate proactive and individualized interventions.

Aviso Predictive Alerts

Aviso programmers connect the platform to an institution's record keeping and online learning management system, such as Blackboard or Moodle. Aviso merges the institution's historical data with data from other peer institutions to create a predictive model that is then applied to the institution's current student information. Specifically for the community college in this study, Aviso uses 23 student-level variables to predict every currently enrolled student's academic performance in each course for which students are registered. Table 3.1 lists all of the variables and their categories that Aviso used to build its predictive model.

Table 3.1

List of Student-Level Variables Used in Aviso's Predictive Analytics

Variable name	Categories
Age	Student age at term start is currently less than or equal to 20 years of age.
	Student age at term start is between 21 and 26 years of age.
	Student age at term start is 27 years of age or older.
Gender	Male
	Female
Race	Student is black / African American.
	Student is Hispanic.
	Student is not black or Hispanic.
Course subject difficulty level	High (e.g. developmental education courses)
	High-moderate (e.g., biology, anthropology, and health care management)
	Low-moderate (e.g., economics, composition, and psychology)
	Low (e.g., history, communications, and physical education)
Course delivery method	Online course delivery
	Seated course delivery
Course level	000 level course
	100 level course
	200 level course
Total number of attempted credit hours	Student is attempting fewer than 6 credits this term.
	Student is attempting between 6 and 9 credits this term.
	Student is attempting between 10 and 11 credits this term.
	Student is attempting 12 or more credits this term.
Adjusted gross income	AGI is missing.
	AGI is less than or equal to \$20,736.
	AGI is greater than \$20,736.
Dependency tax status	Independent tax status
	Tax status missing
	Dependent tax status
FAFSA submission count*	Only 1 or no FAFSA has been received by cc.
	Multiple FAFSA's have been received by cc over the years.
Standardized math tests scores	Math score is missing.
	Math score is equal to 20 or less.
	Math score is greater than 20.

Table 3.1 (continued)

North Carolina diagnostic and assessment test for math	Math placement score is missing.
	Average math placement score is 6 or less.
	Average math placement score is greater than 6 and less than 7.667.
	Average math placement score is 7.667 or greater.
North Carolina diagnostic and assessment test for reading	Reading placement score is missing.
	Reading placement score is 75 or less.
	Reading placement score is greater than 75 and less than 90.
	Reading placement score is 90 or greater.
Awarded transferred coursework credit	Student has had coursework transfer into the community college.
	Student has not had coursework transfer into community college.
Current term free-aid (grants or scholarships)	Student is not receiving grant or scholarship money this term.
	Student is receiving less than \$5,729 in grant or scholarship money this term.
	Student is receiving \$5,729 or more in grant or scholarship money this term.
Current term Pell grant awarded	Student received a Pell grant this term.
	Student did not receive a Pell grant this term.
Previous term free-aid (grants or scholarships)	Student has received grant or scholarship money in at least 2 terms prior to the current term.
	Student has not received grant or scholarship money in at least 2 terms prior to the current term.
Previous course drop history	Student does not have any prior course drops on record, is new, or is returning and has fewer than 5.
	Student is returning with more than 5 drops.
	Student has no attempted credit in last 5 years but has more than 5 drops on record.
Previous course withdrawal history	Student does not have any course withdrawals on record.
	Student is a returning student with some course withdrawals on record.
	Student has no attempted credit in last 5 years but has some course withdrawals on record.
Repeating current course	Student has not taken the current course previously.
	Student has taken the current course previously.
Cumulative GPA	Student does not have previously attempted coursework at CCCC in any of the past 5 academic years.
	Students cumulative GPA is 2.77 or less.
	Students cumulative GPA is between 2.77 and 3.44.
Course non-passing history	Students cumulative GPA is 3.45 or higher.
	Student has a previously registered course with a non-passing grade.
	Student has passing grades on all previously registered courses.

Table 3.1 (continued)

Current term online course registration	Student is registered for an online course this term.
	Student is not registered for an online course this term.

Note: *Due to collinearity with the dependency is missing variable, FAFSA submitted was excluded from the propensity score and later analyses. Aviso provided a list of variables used in its predictive analytics model. The above lists those variables and their categories, but the actual data set variable names were changed to be clearer for the reader. For example, Aviso's name for the variable "crrtrmattered_cat" was changed to "Total Number of Attempted Credit Hours."

As shown in the table, variables include demographics (e.g., age, gender, race, and financial need); academic history (e.g., placement test scores, cumulative GPA, and course drop/withdrawal records); and current academic rigor (e.g., total hours attempted, course difficulty, delivery method, and course level). Using these variables and previous students' comparable performances (obtained via the historical student data from the institution and its peer institutions), Aviso processes each current student data through an algorithm to estimate a student's probability of passing each course successfully, defined as a final course grade equal to or greater than 70%.

The probability for success that the algorithm produces is presented as a predicted grade for each course in which a current student is enrolled. Predicted grades fall within three course performance levels: low, moderate, and high. Low performance corresponds to predicted numerical grades of less than 70; moderate performance corresponds to predicted numerical grades equal to or greater than 70 but less than 86; high performance corresponds to predicted numerical grades equal to or greater than 86. Since the community college in this study uses a 10-point grading scale, a predicted low performance estimates that a student will earn either a D or F in the course. Likewise, predicted moderate performance estimates that a

student will earn either a C or a low B in a course, and predicted high performance estimates that a student will earn either a high B or an A in a course. Table 3.2 displays how the predicted grade ranges align with performance levels. The table also shows that the performance levels and predicted grades are associated with a color-coded course-performance indicator.

Table 3.2

Predicted Course Performances, Numerical Course Grade Ranges, and Course Flags

Predicted Course Performance Level	Predicted Course Grade Range	Course Performance Indicator
Low	score < 70	Red
Moderate	score = 70 but < 86	Yellow
High	score = > 86	Green

Note: The ranges listed are for the grades a student is predicted to earn in a particular course. The prediction is based on algorithms using historical institutional student data applied to current student data. Each predicted grade corresponds to a course performance indicator/flag assigned to each course in which a student is enrolled.

The coaches and other Aviso platform users at the community college do not see the actual predicted grades for the courses in which a student is enrolled. Instead, the predicted grades are denoted as color-coded performance indicators in a student Aviso profile page. Figure 1 provides an example of how a profile page appeared to coaches at the time of this study.

The screenshot shows the AVISO interface with a navigation bar at the top containing 'Home', 'Students', 'Plans', 'Messages', and 'Reports'. The user is logged in as 'Vicky Advisor'. A search bar is present with a 'Filter' button and a 'Clear' button. Below the search bar, there are tabs for 'STUDENTS (7)' and 'MEETING REQUESTS'. A list of students is shown on the left, including Sydney Baker, Daniel Barnes, Hunter Gonzales, Joseph Henderson, and Cadena Parker. The main profile for Sydney Baker is displayed, showing her name, photo, and a yellow dot next to her name. Below the profile, there are tabs for 'Profile', 'Term', 'Transcript', 'Test Scores', 'Finances', 'Notes', 'Meetings', and 'Documents'. The 'Term' dropdown is set to 'SPRING 2015 - Registered'. A table shows course information for 'BUS1150A 01 Statistics' with a yellow dot next to the course name. The table includes fields for Instructor, Registration Status, Current Grade, Credit, Last Login Date, and Last Assignment Submitted.

BUS1150A 01 Statistics	
Instructor	Fran Faculty
Registration Status	Registered
Current Grade	83.70
Credit	4.00
Last Login Date	September 29, 2013 1:23 AM
Last Assignment Submitted	September 20, 2013 2:12 AM

Figure 1. With permission, this graphic was taken from a presentation that the director of the student-success coaching program uses for professional development training at the community college. This screen shot displays a mock-student’s account profile as coaches see it in Aviso. The yellow dot to the right of the student’s course indicates the student’s predicted course performance. The yellow dot to the right of the student’s name matches the student’s lowest predicted course performance.

The performance indicator is a small colored circle, a dot, beside each course in which a student is listed as enrolled in the “term” tab. The color of the dot corresponds to the student’s predicted academic performance for that course, as Table 3.2 displays. In the example-student profile page of Figure 1, the performance indicator is the yellow dot placed to the far right of the course name. The yellow dot is how Aviso visually indicates to its users that the student is predicted to perform moderately—that is, to earn either a C or low B—in this course. In the vernacular of student-success coaches at the community college in this study, the color-coded dots for the course-level and student-level performance indicators are referred to as flags. If a course has a green dot, coaches refer to that course being flagged green for the student. If students have a yellow dot beside their name, the students are

referred to as being flagged yellow or, simply, as yellow-flagged students. In the Figure 1 example, the student's BUS 115 course is flagged as yellow. Because this example-student is enrolled in only one course, her student-level yellow flag—the yellow dot beside the student's name—matches the yellow flag of the course. The color dot beside a student's name always corresponds to the student's lowest predicted course grade. It does not matter how well the student is predicted to perform academically in the other courses.

Students will have a green dot beside their name only if they have been predicted to earn a grade of 86 or higher for all of the courses in which they are enrolled. If students are predicted to earn a grade less than 86 in any of their courses, the students will not have a green dot beside their names. Several combinations of grade predictions can occur across student course schedules, and Table 3.3 displays several example combinations of predicted course grades, associated color-coded course performance indicators, and the overall student-level performance indicator color.

Table 3.3

Example Table of Predicted Course Grades Relationship to Student Flags

Student	Course Name	Predicted Course Grade	Course Flag	Average of Predicted Course Grades	Student Flag
Mathew	CJC111	88%	Green/=>.86		
Mathew	PSY150	92%	Green/=>.86		
Mathew	CJC112	86%	Green/=>.86	90%	Green
Mathew	CJC160	92%	Green/=>.86		
Mathew	CJC231	89%	Green/=>.86		
Greg	PED110	93%	Green/=>.86		
Greg	ENG111	84%	Yellow/=,7-<.86		
Greg	GEL111	79%	Yellow/=,7-<.86	87%	Yellow
Greg	SPA111	89%	Green/=>.86		
Greg	SOC210	89%	Green/=>.86		
José	PSY150	84%	Yellow/=,7-<.86		
José	MAT171	84%	Yellow/=,7-<.86		
José	BIO110	76%	Yellow/=,7-<.86	82%	Yellow
José	ECO251	84%	Yellow/=,7-<.86		
Claudia	DMA020	55%	Red/<.69		
Claudia	ACA115	81%	Yellow/=,7-<.86		
Claudia	DMA030	55%	Red/<.69		
Claudia	PSY241	87%	Green/=>.86	75%	Red
Claudia	DRE098	91%	Green/=>.86		
Claudia	HUM122	81%	Yellow/=,7-<.86		
Xander	ENG125	63%	Red/<.69		
Xander	SPA111	63%	Red/<.69	63%	Red
Xander	MAT143	63%	Red/<.69		

Note: The above table lists five example variations of predicted course grades across students' schedules. As displayed in the table, students could have a mix of predicted grades; however, their student-level performance dot directly corresponds to the course(s) for which they have the lowest predicted grade. For example, some of Greg's courses have been flagged green and some have been flagged yellow. As a student, though, Greg is flagged as yellow because he has some yellow-flagged courses. Claudia also has green- and yellow-flagged courses, but she is considered a red-flagged student since she has two red-flagged courses.

In Table 3.3, the student Mathew exemplifies a green-flagged student (heretofore, a green student). For each course in which he is enrolled, he is predicted to earn a course grade of 86 or higher. In term tab of his Aviso profile, each course would be flagged with a green dot, and, thus, his profile would also be flagged with a green dot beside his name. Greg, however, is a yellow-flagged student (heretofore, a yellow student) because he is predicted to earn grades equal to or higher than 70 but less than 86 in two of his five courses. Despite being predicted to earn 86 or higher in three of his five courses, Greg is still flagged as yellow. José represents a yellow student who is only predicted to earn grades equal to or higher than 70 but less than 86 in each of his courses. Each course is flagged yellow, and José's profile is flagged yellow. Claudia illustrates an interesting mix of course grade predictions. Two of her six courses are flagged green, but the other four courses are flagged as yellow or red (two of each flag). Because two of her courses are flagged red, her profile is flagged red. Claudia is a red-flagged student (heretofore, a red student) despite being predicted to perform well (flagged green) in two of her six courses. Finally, Xander is predicted to earn less than 70 in each of his three courses, so each course is flagged red and his profile is also flagged red.

Table 3.3 demonstrates how yellow and red students can have a mix of grade predictions while green students must be predicted to earn grades 86 or higher in all of their courses. The table also contains an average of predicted course grades. While these averages are not in the Aviso platform or its data, the averages display how students' averages of predicted course performances can be similar even though students can be flagged very differently and, thus, provided different support experiences with the coaches. For example,

Mathew's average of predicted course grades is 90% while Greg's is only 3 percentage points lower at 87%. Mathew's and Greg's student-level profile flags, however, are different, indicating that Greg might need student-success coaching to improve his outcomes but that Mathew likely does not need coaching. An analogous comparison can be made between Greg and José, whose averages only differ by 5 percentage points, but both of whom will be offered the proactive student-success coaching that Mathew will not be offered. Claudia presents an interesting case, too, because the average of her predicted grades is pulled down by the two developmental math courses (DMAs) in which she is enrolled. If it were not for the two low grade predictions (both 55%), Claudia's average might be more similar to Greg's than it actually is. Nonetheless, Claudia will not be proactively contacted by a student-success coach because she has been flagged as red. Unlike the other students, Xander's course grade predictions are all low, and his average is more than 10 percentage points lower than the next highest average, Claudia's. Xander and Claudia, however, will be considered the same performance-type student—red students—since they both have courses flagged red.

Mathew is a “pure” green student; José is a pure yellow student; and Xander is a pure red student. Aviso's predictive analytics, though, have assigned a mix of course-grade predictions for Greg and Claudia. Both Greg and Claudia have at least two green-flagged courses, but because Greg does not have any red-flagged courses, Greg is flagged as yellow while Claudia is flagged as red because of her two red-flagged courses. In short, students are flagged at the student-level profile based on the lowest course-grade prediction that Aviso has estimated for them despite any higher predictions made for their other courses.

Aviso-Generated Student Groups

While the above discussion articulates the connection between course-grade predictions and student-level performance flags, Table 3.4 describes the three student groups created by the student-level performance flags in this study: green, yellow, and red. While the second, third, and fourth columns provide the means for the variables listed in the first column, the fifth and sixth columns provide the absolute differences between green and yellow students and between yellow and red students, respectively. The table rows are divided into four sections. The first section represents variables associated with the course-grade predictions. The second section contains some of the means for the demographic data of each group. The third section displays academic preparation variables, and the fourth section presents academic performance variables. While the table does not include all of the variables available for the students, it does provide the means for several important and representative variables across the groups.

Table 3.4

Group Means for a Sample of Variables Used in Aviso's Predictive Analytics

Variable	Green (n=2,525)	Yellow (n=1,224)	Red (n=772)	Green/Yellow Difference	Yellow/Red Difference
Average of predicted grades	93.1	82.9	65.6	10.2	17.3
Green course count	3.1	1.2	0.7	1.9	0.5
Yellow course count	0.0	1.6	1.0	1.6	0.6
Red course count	0.0	0.0	2.0	0.0	2.0
Female	67.9%	55.4%	57.0%	12.6%	1.6%
Age	26.3	22.22	23.38	4.12	1.15
Non-white	28.7%	44.5%	58.2%	15.9%	13.6%
Dependent student	19.7%	27.8%	43.0%	8.1%	15.2%
Received Pell Grant	65.5%	65.6%	46.1%	0.1%	19.5%

Table 3.4 (continued)

No math placement score	79.5%	68.1%	39.0%	11.5%	29.1%
Average math placement score= ≤ 6	9.61%	22.8%	55.8%	13.2%	33.0%
No reading placement score	66.9%	64.2%	44.2%	2.7%	20.0%
Reading placement score >90	13.5%	6.9%	6.6%	6.6%	0.3%
Cumulative GPA	3.28	2.35	1.94	0.92	0.41
Passed all previous courses	88.4%	74.6%	50.3%	13.8%	24.3%
No dropped courses	81.6%	80.3%	65.9%	1.4%	14.4%
No withdrawals	82.4%	71.2%	50.5%	11.2%	20.7%
Repeating courses	11.2%	17.0%	34.1%	5.8%	17.1%
Total credit hours	9.4	8.3	9.0	1.16	0.7
High-difficulty course count	0.0	0.1	0.9	0.1	0.1
Low-difficulty course count	1.7	0.8	0.9	0.9	0.1

Note: The second through third columns present the mean of each variable listed for each group. The fifth column provides the absolute difference between green and yellow groups, and the sixth column provides the absolute difference between variable means for the yellow and red groups.

Not surprisingly, the green-students mean of average of predicted grades was higher grade than the means of both yellow and red students. More interesting, though, is that the means of average predicted grades for green and yellow students are more similar than the means for yellow and red students; 10.2-point and 17.3-point differences respectively. Based on course counts, green and yellow students seem to enroll in the same number of courses on average while red students enroll in one more course on average than green and yellow students. The similarities between green-student and yellow-student means are found for the majority of the variables in Table 3.4 even though, on average, students in each classification are enrolled in at least one green-flagged course for which the predicted grade is 86 or higher.

The few variables for which green-student and yellow-student means differ the most tend to be the same variables that yellow-student and red-students means either differ about the same or in greater magnitude. The exception is the percentage of female students in each group. Green students tend to be more female than do yellow and red students, and the proportions of females in the yellow and red groups are about the same: 55.4% for yellow and 57% for red. Taken together, the means for the demographic variables suggest that slightly older, white, female students who have an independent tax status and who received Pell Grant awards are more often flagged as high-performing green students than younger, non-white, male students who have a dependent tax status and who did not receive Pell Grant awards. Stated differently, green students tend to be more female and white than do yellow or red students.

Regarding the academic preparation variables, green students tend not to have placement test scores, suggesting that they had stronger academic preparation in high school than yellow and red students. Because the state-wide community college system under which the community college in this study operates waives placement tests for high school graduates meeting a set of requirements (e.g., high school GPA and high school math course selections or SAT and ACT scores), the 79.5% of green students who on average lack math placement test scores suggests that those students met all the waiver requirements. The same could be stated for the 68.1% of yellow students who also lack math placement test scores. The relatively low percentage of red students who lack math placement test scores indicates that the average red student is the least academically prepared for college-level math courses.

Since students must earn scores of 7 or higher on each of the first six math placement tests to be eligible to enroll in college-level math courses, the 55.8% of red students who have an average math placement score equal to or less than 6 further implies the average red-student is not academically prepared for college-level math courses. Once again, though, the difference in means between the green and yellow students is much less than that of yellow and red students. For similar reasons as those of the math placement test scores, the means for the reading placement test scores also supports the trend of green and yellow students tending to be more similar than yellow and red students are. As Table 3.4 indicates the tendency for green and yellow students to be more alike than yellow and red students continues in the rest of the variables.

To augment Table 3.4's descriptive statistics for the student groups Aviso's flags created, Table 3.5 provides the percentages of matches between student groups' predicted and earned grades to illustrate the accuracy of course grade predictions. The accuracy in the table is noted by the bold numbers. If the predictions were perfect, then the bold numbers would equal the sum of the percentages in that row. However, the trend in these bold percentages indicates that the predictions were imperfect. For example, green students were predicted to earn an A in 83% of their courses but green students only earned A's in 45% of their courses for which they were predicted to earn A's. Furthermore, green students earned B's in 23% of their courses for which they were predicted to earn A's. While imperfect the predicted grades seem to categorize students at least somewhat accurately: green students mostly earned A's and B's; yellow students mostly earned A's, B's, and C's; and red

students earned a mix of grades but mostly either B's or F's. However, since the yellow-students course performances should have been influenced by student-success coaching, the effect of the intervention should be considered when interpreting the percentages for yellow-students. For example, the yellow student trends suggest that they earned better than expected grades in courses for which they were predicted to earn B's or C's, but that they earned worse than expected grades in course for which they were predicted to earn A's. The trends seem to conflict with each other—if effective, the impact of the intervention should be positive on all course performances.

Table 3.5

Percentages for Matches between Predicted- and Earned-Grades by Student Category

Student Category	Predicted Grade	Earned Grade Percentages					Earned Grade N					Total N
		A (100-90)	B (89-80)	C (79-70)	D (69-60)	F (<60)	A (100-90)	B(89-80)	C (79-70)	D (69-60)	F (<60)	
Green	A (100-90)	45%	23%	9%	2%	3%	3,503	1,792	668	169	210	6,342
	B (89-86)	8%	5%	3%	1%	1%	644	419	229	86	113	1,491
	Spearman's rho (n=7833)	0.12										
Yellow	A (100-90)	10%	8%	3%	1%	1%	339	271	115	20	44	789
	B (89-86)	20%	16%	10%	3%	5%	710	571	345	109	163	1,898
	C (85-70)	7%	8%	5%	1%	3%	262	266	162	47	123	860
	Spearman's rho (n=3547)	0.12										
Red	A (100-90)	2%	3%	1%	0%	1%	71	77	28	14	24	214
	B (89-86)	5%	6%	4%	1%	4%	134	179	116	41	110	580
	C (85-70)	4%	6%	3%	2%	3%	110	158	92	47	95	502
	D (69-60)	4%	8%	4%	2%	5%	108	238	123	50	152	671
	F (<60)	2%	12%	2%	1%	13%	64	354	66	33	368	885
	Spearman's rho (n=2852)	0.20										

Note. The percentages represent the proportion of courses for which students within a group who were predicted to earn that specific grade earned that specific grade. For example, green students who were predicted to earn grades of A actually earned a grade of A in 3,503 of the 7,833 courses that green students completed.

Proactive Student-Success Coaching

The academic year from which this study's data comes was the first year that the community college utilized Aviso's predictive analytics to focus the efforts of student-success coaches. Prior to that year, the community college used only the reactive student-monitoring functions of the Aviso system. As part of the program implementation, the student-success coaches met weekly to discuss priorities and progress, save for a couple of missed weeks during the semester. In the Fall 2015 semester, the coaches also attended two specified professional development sessions on advising and an off-campus retreat for student-success coaching staff development. During some of the coaches' weekly meetings, representatives from other college areas presented on their area-specific services, and they had at least one meeting dedicated to professional development session on Appreciative Advising (for descriptions of Appreciative Advising see Bloom, Hutson, He, & Konkle, 2013; He, & Hutson, 2016; and He, Stanback, & Bloom, 2012).

Because the college had limited capacity to address all predicted student academic issues, student-success coaches proactively offered academic and institutional support to only yellow students. The college determined that proactively supporting the yellow students would be the most efficient use of its resources although that support would not be denied to student-initiated requests for assistance from green and red students. Table 3.6 provides a timeline for the services the coaches provided to the student groups.

Table 3.6

Timeline for Student-Success Coaching Activities

Month	Yellow students	Green students	Red students
August	<ul style="list-style-type: none"> All students contacted via introductory email, followed up with phone calls. Coaching role explained. College services explained and offered as needed. In-person appointments arranged as needed. 	<ul style="list-style-type: none"> Student-initiated support requests addressed (e.g., walk-ins for tutoring). 	<ul style="list-style-type: none"> Student-initiated support requests addressed (e.g., walk-ins for tutoring).
September	<ul style="list-style-type: none"> Students monitored and re-contacted as needed. Attendance and low grades issued addressed. Positive achievement messages sent for high grades. Birthday messages emailed as appropriate. In-person appointments and other support services. 	<ul style="list-style-type: none"> Student-initiated support requests addressed (e.g., walk-ins for tutoring). 	<ul style="list-style-type: none"> Student-initiated support requests addressed (e.g., walk-ins for tutoring).
October	<ul style="list-style-type: none"> Students monitored and re-contacted as needed. Attendance and low grades issued addressed. Positive achievement messages sent for high grades. General messages encouraging attendance emailed. Birthday messages emailed as appropriate. In-person appointments and other support. All system- and instructor-generated alerts addressed. Pre-registration information emailed. 	<ul style="list-style-type: none"> Pre-registration information emailed. Student-initiated support requests addressed (e.g., walk-ins for tutoring). 	<ul style="list-style-type: none"> After all yellow-student issues addressed, coaches contact students about system- and instructor-generated alerts. Academic support services offered for alerts. Pre-registration information emailed. Student-initiated support requests addressed (e.g., walk-ins for tutoring).
November	<ul style="list-style-type: none"> Students monitored and re-contacted as needed. Attendance and low grades issued are addressed. Positive achievement messages sent for high grades. General messages encouraging attendance are emailed. Birthday messages emailed as appropriate. In-person appointments and other support. All system- and instructor-generated alerts addressed. Alerts prioritized over all other coach responsibilities. 	<ul style="list-style-type: none"> Academic support services offered for alerts. Student-initiated support requests addressed (e.g., walk-ins for tutoring). 	<ul style="list-style-type: none"> After all yellow-student issues addressed, coaches contact students about system- and instructor-generated alerts. Academic support services offered for alerts. Student-initiated support requests addressed (e.g., walk-ins for tutoring).
December	<ul style="list-style-type: none"> Services continue as above. Overall GPA alerts addressed. Final grade achievements recognized. 	<ul style="list-style-type: none"> Services continue as above. Overall GPA alerts addressed. Final grade achievements recognized. 	<ul style="list-style-type: none"> Services continue as above. Overall GPA alerts addressed. Final grade achievements recognized.

Note. The table provides an abbreviated list of actions implement by student-success coaches throughout the semester.

Student-success coaches generated caseloads of yellow students using the Aviso platform, and the caseloads were distributed among the coaches. As Table 3.6 displays, student-success coaches provided more enhanced support to yellow students than to either green or red students throughout the semester. After the semester started in mid-August, coaches contacted students in their caseloads within the first two weeks of the semester. Coaches first contacted their caseloads through emails in which the coaches introduced themselves and offered initial help as needed. The coaches followed those introductory emails with phone calls during which they explained their roles as coaches and discussed any obstacles to academic success that the Aviso platform indicated that the students might have. The coaches also arranged in-person appointments if the students were interested in and willing to meet.

Students' potential obstacles appear as "success measures" in a pop-up window that is displayed when coaches click on the performance-indicator dot beside a course. Figure 2 displays how this window appears to coaches.

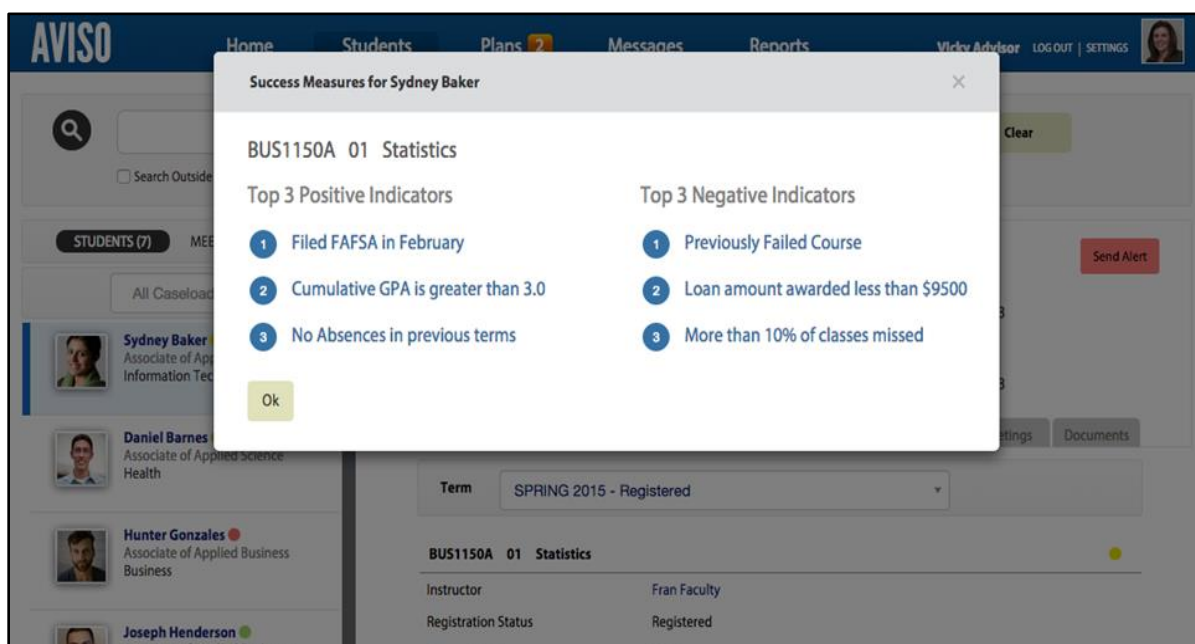


Figure 2. With permission, this graphic was taken from a presentation that the director of student-success coaching used for professional development training at the community college. The screen shot of a mock-student profile displays the top three positive and negative indicators for a student’s performance in a particular course. This pop-up window appears when coaches click on the course-performance indicator (the dot) beside a course in the Aviso platform.

It is important to note that students do not have access to this information; only appropriate college employees have access to these success measures. Coaches use these success measures to individualize support for each student. Figure 2 displays the pop-up window that appears for the example-student from Figure 1. In this window, three positive and three negative indicators are provided. These indicators correspond to variables used in Aviso’s predictive analytic models.

In the case of the example-student, the primary indicators/variables for the grade prediction include previous academic performance (cumulative GPA balanced against course

failure) and demographic information (FAFSA completed on time but award was less than a particular amount-threshold). Coaches use such information to provide individualized coordination of academic and institutional support to students. For the example-student, the coach would likely focus on the “previously failed course” indicator by discussing with the student why she might have failed the course and then suggesting methods to improve her performance in the current semester. Some of the suggestions might involve improving academic behaviors such as study habits, class attendance, and increased interaction with the course instructor. The coach might also arrange a tutor for the student or direct the student to supplemental instruction sessions.

Not all of the discussion concerns estimated negative indicators. A student-success coach working with this example-student would also recognize the student’s positive indicators: a cumulative GPA greater than 3.0 and no absences in the previous term. However, coaches do not necessarily use all of the information that Aviso provides. Since there is little a coach can do about the student’s financial aid award, the coach would unlikely address that indicator unless the student requested financial aid information. For the sake of the most immediate academic concerns, coaches tended to focus on actionable information that could improve student outcomes.

The goals of the student-success coach interactions with yellow-flagged caseload students were to circumvent obstacles to academic success, to reinforce productive academic behaviors, and to become the single-point of contact for support services. To facilitate these goals, coaches monitored students through the Aviso platform and initiated contact as

needed. As the semester continued, coaches attempted to develop relationships with students in their caseloads by emailing them positive achievement messages about attendance and high grades as well as by emailing personal messages, such as birthday wishes, when appropriate. The Aviso system prompted coaches to send some of these emails, and the system automated some of them, such as emails about high grades.

Coaches also continued holding in-person appointments with students who opt-in and take advantage of the coaches' assistance. During these appointments, coaches addressed any immediate concerns and achievements as well as discussed the alignment of students' current academic actions to their long-term goals. Specifically, coaches discussed students' academic plans and career goals to ensure students' current academic programs connected to their anticipated employment and future educational needs (e.g., transfer to four-year institution or graduate school). Coaches helped students develop and amend academic action plans as needed. The underlying concept supporting such conversations was that students would be more engaged with their current academic work if they understood how successfully completing their current courses would help them achieve their future goals.

The above discussions occurred throughout the semester but were the focus of most early interactions, especially in August, September, and early October. Before the academic year from which this study's data were collected, coaches used the Aviso system to react to students' poor performance reports, such as low mid-term grades or reports of attendance issues. Prior to the introduction of Aviso's predictive analytics, coaches mostly either helped students who came into the community college's academic success centers or reacted to

students' poor performance reports. After Aviso included predictive analytics in the services provided to the community college, the coaches were able to initiate analytics-informed coordinated student support services within the first two weeks of the semester.

By mid-October, though, enough academic work had been submitted and graded that Aviso could generate grade reports from data posted in the college's learning management system (Blackboard). Additionally, course attendance and midterm grades were posted in October to the college's record keeping system, from which Aviso also generated reports. At that midterm point in the semester, coaches also started addressing reactive alerts that Aviso generated from these data sources. Typical reactive alerts concerned low midterm grades or infrequent course attendance and Blackboard course site logins. Coaches prioritized reactive alerts for yellow students, and coaches only addressed alerts for red students if the coaches had addressed all issues with their yellow-student caseloads. While occasionally alerts were generated for green students, coaches were unable to address alerts for green students before new alerts for yellow students were generated. To be clear, coaches did not resolve alerts for green students, and coaches were often unable to address the majority of red student alerts.

As discussed earlier, coaches assisted non-yellow students prior to the reactive-alerts in October only if those students initiated the request for service. For example, if a green or red student entered one of the college's academic assistance centers seeking a tutor for a writing course, the center's staff arranged for the student a tutor or an appointment in one of the college's writing centers. Students seeking support services were not denied the available services, but coaches only proactively contacted yellow students in August, September, and

early October. After reactive alert reports were generated in October, though, coaches balanced their focus on proactively advising and supporting yellow students with resolving system-generated alerts—first for yellow students and then for red students. The change in focus from proactively addressing potential issues to reactively resolving actual issues was the point in the semester at which Aviso was used most like other student-monitoring systems. Until that point, student-success coaches primarily utilized Aviso’s predictive analytics to advise students through potential impediments to their academic success. After that point, coaches used all of Aviso’s functions to support students who either were on a system-generated report or who initiated service by coming to an academic assistance center.

This shift in focus occurred in the latter part of October because the semester midterm point was in late October. From late October through early December, student-success coaches did not vary their activities much from the above description, except that pre-registration and registration information was sent to all students. As the single-point of contact for yellow students, coaches helped yellow students plan their next semester schedules in collaboration with the students’ assigned faculty advisors during the semester’s pre-registration and registration periods. Coaches ensured that their yellow caseload students registered for the correct courses as approved by students’ faculty advisors. After most registrations were completed in late November, coaches prioritized resolving system-alerts over their other coaching responsibilities. Finally, after final grades were posted in December, automated emails were sent to students about positive final grade achievements

and student-success coaches emailed all students about low cumulative GPA alerts and yellow students about spring-semester schedule changes as needed.

Theory of Change for Proactive Student-Success Coaching

Figure 3 displays the components for the Theory of Change Model for the Proactive Student-Success Coaching intervention. The graphic represents how proactive student-success coaching affects students across time. The model also shows the relationships among the components as students progress through a semester and an academic year. Not shown in the model and beyond the distal outcomes of GPA and fall-to-spring persistence, the ultimate goal of the intervention is for students to continue their education to graduation. The underlying assumption of the model is that offering proactive student-success coaching and coordinated support services to students predicted to earn grades equal to or higher than 70 but less than 86—yellow students—will facilitate for these students improved performance in courses, academic integration, and knowledge and use of services, and that these improved proximal outcomes should positively affect students' GPA and persistence.

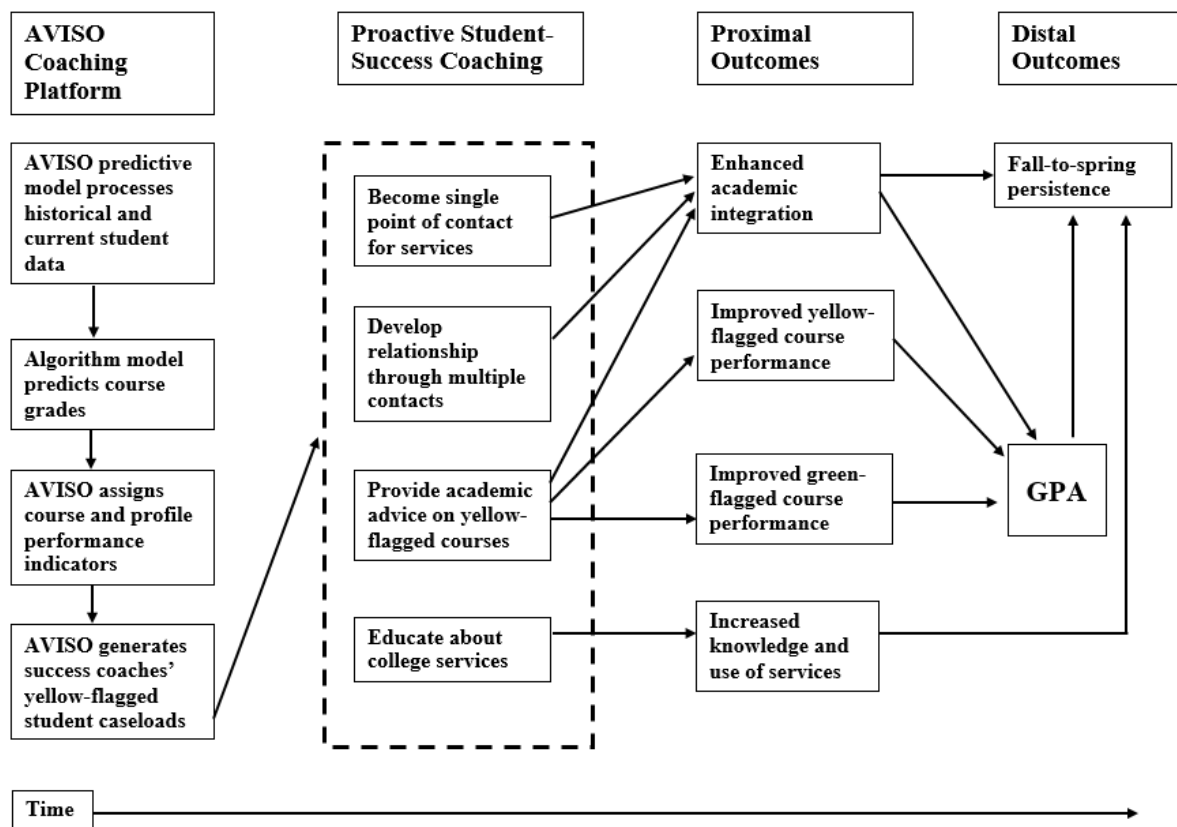


Figure 3. Theory of Change Model for Proactive Student-Success Coaching.

Consistent with most models and theories regarding student success (Pascarella & Terenzini, 2005), students' pre-entry attributes (see Table 3.1) are considered prior to offering the intervention when historical data from the community college and some of its peer institutions are used to yield insights into why students succeed in general and in particular at the community college in this study. Aviso builds its algorithms based on those data sources and then compares previous students' characteristics and performances with current students' characteristics to predict the course performances of currently enrolled students. Because statistical analyses typically suggest that past trends are indicative of future outcomes, the

application of historical student data to current student data should accurately recognize students who would benefit most from success coaching (yellow), students who likely do not need coaching (green), and students who will be unlikely to overcome impediments to successful course completion (red). Coaches can then use Aviso's data-informed student profiles, indicators, and monitoring functions to prioritize proactive interventions with those students who might otherwise be as likely to succeed as to fail (yellow students).

The segment of the model labeled "Proactive Student-Success Coaching" represents the essential activities portion of the model. The individualized and proactive interventions that occur in this segment are assumed to work because Aviso's predictive analytics inform the student-success coaching. Similar to how recommendation engines, such as Google and Amazon, can predict users' behaviors and then attempt to influence those behaviors, student-success coaches use Aviso's predictive analytics to understand students' potential academic behaviors and then attempt to guide students to avoid detrimental actions and to adopt productive academic behaviors. For example, if Aviso identified academic preparation in math (via math placement score variables) as a potential impediment for a student, the assumption is that the student will struggle in courses that require competency in math. Relying on this assumption, a coach can suggest that a student use one of the college's STEM labs or arrange for subject-area tutoring to prevent the student from developing an academic issue with a particular math-intensive course. In this way, proactive student-success coaching is analogous to preventative medicine: much like how adequate exercise and healthy diets typically should prevent heart disease, coordinated academic assistance

from the start of the semester should mitigate a student's learning difficulties in a course. Assuming Aviso's predictive analytics accurately identify potential issues, the system provides coaches with analytics-informed direction in how to support the students at the start of the semester rather than midway through or after the semester ends.

Providing academic advice for students' yellow-flagged courses and arranging for academic support services are two primary student-success coaching activities that should improve student performance in yellow-flagged courses. The advice and support for yellow-flagged courses should also translate into improved performance in green-flagged courses because productive academic behaviors, such as seeking help with courses and on-time submission of course work, are transferable actions applicable to more than just the yellow-flagged courses (recall that yellow-flagged students have no red courses). Improved academic performance in yellow- and green-flagged courses should yield increased GPAs for proactively coached students. Better-than-predicted academic performance should reinforce students' commitments to their educational goals and encourage them to continue enrollment in the next semester.

The coaching provided for yellow-flagged courses should also enhance students' academic integration. For example, if the coach's advice includes setting appointments with the instructor of a course in which a student is struggling and that student does so, the student will have increased interactions with faculty members. The more interactions the student has with faculty members, the potential for the student's successful academic integration

improves; that is, student-faculty interactions increase students' sense of belonging to an institution (Pascarella and Terenzini, 2005).

Other activities of student-success coaches include becoming the single-point of contact for yellow students, developing relationships with them, and educating them about college services. Instead of transferring students from one college staff member to another depending on the nature of the issue, student-success coaches facilitate much of the information-gathering for the students: coaches help students define the needed services or information, determine which college area is responsible, and then coordinate the delivery of that service or information. In so doing, coaches remove obstacles that could prevent students from getting the assistance or information they might need. If a coach and a student determine that the student needs help writing essays for a course, the coach does not just suggest that the student to go to a writing center. Rather, the student-success coaches will schedule an appointment for the student in the writing center and, likely, direct the student to additional online resources. As appropriate, the coach will later follow up with the student to learn how the student's writing is progressing. The initial coordination of services and later follow-up on students' actions and outcomes expedite access to support and instill a sense of accountability for the student.

The multiple interactions involved in the above scenario help student-success coaches develop relationships with their caseloads of yellow students. In doing so, the assumption is that students will develop a sense of belonging to the institution and will integrate into the academic setting more easily than they would without the coaching. Successful academic

integration is important at all levels of education but is likely more important in the community college setting than others because almost all community colleges are commuter institutions. Since community college students do not typically live on or, necessarily, near their college campuses, successful academic integration in community colleges is assumed to be formative in students' achievement of their educational goals. Similar to how increased faculty interactions help students adopt "normative attitudes and values" important to their academic success (Pascarella & Terenzini, 2005, p. 54), the student-success coaches reinforce the academic integration process for students in their caseloads. Strengthened commitment to educational goals follows students' successful academic integration and should result in their semester-to-semester persistence.

As yellow students encounter non-academic issues, such as financial-aid verifications and student-government activities, student-success coaches educate students about the appropriate college services related with such issues. The assumption is that the more students are educated about college services, the more students will understand and utilize those college services. For example, if a student is selected for financial-aid verification, coaches will not only inform the student that about 25% of the college's students are selected every year in accordance with federal regulations and that selection does not indicate that funding is denied, the coaches will also either help the student compile the necessary verification documents or will arrange a meeting for the student with one of the college's financial aid representatives to complete the verification process. With the help of the student-success coach, understanding and completing the financial-aid verification removes a

potential obstacle—financial support—for the student to continue current term enrollment and to re-enroll in the next semester.

Implemented together, the proactive student-success coaching activities should increase the probability that the proximal outcomes occur because they are collectively influencing students' productive integration into the academic system of the community college and their academic performance in their courses. These proximal outcomes, in turn, should positively impact the distal outcomes. If students successfully integrated into the academic system of the college and perform well in their courses, their semester GPAs (and cumulative) should be higher than they would be without student-success coaching. Furthermore, enhanced academic integration, higher-than-predicted GPAs, and increased college-services utilization should increase the probability that students will persist from the fall to the spring semester because students who are academically successful typically continue to persist (Pascarella, and Terenzini, 2005).

The proactive student-success coaching theory of change model illustrates how and why the intervention should be successful in helping students realize the proximal and distal outcomes. The Aviso platform analyzes student data and predicts academic performance. Student-success coaches rely on these predictions and the success indicators to personalize their coaching interventions. In turn, these interventions should facilitate successful student academic integration, course completion, and use of college services. Thus, the greater-than-predicted improvement of these proximal outcomes should yield greater-than-predicted distal outcomes.

CHAPTER 4: METHODOLOGY

This study examined the effects of proactive student-success coaching offered to students whom the Aviso system flagged as yellow because of their predicted course performances. While some research has addressed reactive interventions of early-alert systems (Bruce et al., 2011; Faulconer et al., 2014; Hanover Research, 2014; Hudson, 2006; and Johnson, 2000), little research has been conducted on proactive interventions of any type. Moreover, of the studies that have investigated proactive interventions, only a couple of those have adhered to experimental or quasi-experimental designs (Richie & Hargrove, 2004; and Bettinger & Baker, 2014). As such, the literature lacks sufficient information about the effects of proactive student-success coaching on student outcomes. To contribute evidence to the literature, I used quasi-experimental techniques to address the primary questions of this study: what were the effects of offering proactive student-success coaching on the GPAs and the fall-to-spring persistence of yellow-flagged students compared to other students?

In this chapter, I discuss the research design, institutional setting, participants, variables, data collection, and propensity score analysis.

Research Design

Because the community college in this study had already offered treatment to all eligible students, a randomized controlled trial experiment could not be conducted to test the effects of offering student-success coaching to students. Instead, I used a quasi-experimental design that relied on propensity score analysis to assemble comparable groups for later regression analyses, approximating the treatment and the control groups created in

randomized controlled trial experiments. Once the data were available, I explored the use of a few quasi-experimental methods that are prevalent randomized-controlled-trial alternatives in the literature: propensity score matching (Caliendo & Kopeinig, 2008; Ho, Imai, King, & Stuart, 2007; and Khandker et al., 2010), coarsened exact matching (Iacus, King, & Porro, 2011), and inverse probability of treatment weighing (Austin, 2011; Austin & Stuart, 2015). Based on the available data, I determined that inverse probability of treatment weighing would yield more balanced comparison groups than would the other two methods.

Other quasi-experimental designs were inappropriate to use in this study. For example, regression discontinuity requires a specific numerical cut-off point(s) to determine participation and non-participation. Proactive student-success coaching was only offered to yellow students, who were designated as yellow because they had yellow-flagged courses (and maybe some green-flagged courses) but no red-flagged courses. Aviso's predictive analytics model did not calculate an overall semester performance score for a student; instead, the system estimated the numerical grade for each course in which a student was enrolled. Almost every student had multiple cut-off points: one per course. Typically, regression discontinuity requires a single or only a few cut-off points to determine participation. In the case of this study's data, there were just too many forcing variables to use this method effectively. The instrumental variable estimation approach is another useful quasi-experimental design. However, the method could not be used in this study because identifying a variable that was not both highly correlated with the designation of students as yellow and the outcome variables of semester GPA and fall-to-spring persistence was

problematic. The variables in Aviso’s models that determine selection into treatment (flagged as yellow) are theoretically highly correlated with outcomes, which is why Aviso used them in their predictive algorithms.

I relied on propensity score analysis of the data to apply the inverse probability of treatment weighting technique to the groups. The use of this technique required the availability of observable characteristics upon which to compare groups. Aviso provided me all the variables it had obtained from the college; however, Aviso’s predictive-analytics model used only 23 of those variables. In addition to the variables in Aviso’s model, I also created and used the average of a student’s predicted grades (and its square as a quadratic term) to create a logit model for the probability of being flagged yellow and, thus, being eligible for the offer of treatment.

The model produced for each student a “propensity score: $P(X) = \Pr(T = 1|X)$ ” (Khandker et al., 2010, p. 55), which was used to assign weights to students. Whereas in the propensity score matching technique treated and untreated units of observations are matched with the propensity scores, the inverse probability of treatment weighting technique weights participant observations with the inverse probability of participants being treated, defined by Austin and Stuart (2015) as

$$w = \frac{Z}{e} + \frac{1-Z}{1-e}$$

Defined this way, w is the inverse probability of treatment weight calculated with Z representing assignment to treatment (1 for treated, 0 for untreated) and e being the propensity score defined above ($P(X)$). Otherwise stated, “each subject’s weight is equal to

the inverse of the probability of receiving treatment that the subject received” (Austin & Stuart, 2015). The weights generated in this study were used to create artificially similar comparison groups within each data sample.

To use propensity score analysis, two assumptions must be justified to estimate the effect of intervention: the assumption of conditional independence (also known as unconfoundness) and the assumption of common support (Caliendo & Kopeinig, 2008; and Khandker et al., 2010).

According to Khandker et al. (2010), “conditional independence states that given a set of observable covariates X that are not affected by treatment, potential outcomes Y are independent of treatment assignment T ” (Khandker et al., 2010, p.55). In the case of this study, students were assigned to the treatment based on a predictive model developed from aggregated historical data of other students. That model of performance was then applied to current students’ data to estimate the probable performance of the current students in each of their courses. In effect, Aviso predicted course grades for current students based on the outcomes of previous students with whom the current students had similar observable characteristics. Because I had access to all of the variables used to predict course grades and, thus, selection into treatment, there were not any unobserved characteristics affecting the categorization of participants as yellow. Because Aviso used categorical and ordinal variables to represent student observations, such as a categorical variable for age when the continuous version of the observation was available, I created dummy variables for most of Aviso’s original variables, resulting in the 61 variables provided in Table 4.1 below.

Table 4.1

Complete List of Variables Used in Propensity Score and Regression Analyses

Name	Source	Explanation
Propensity score	Generated	The propensity score for being selected into treatment
Aviso average model score	Generated	Average of predicted numerical grades for each student
Aviso average model score squared	Generated	Quadratic term of the average model score
Female	Categorical	Female = 1, Male = 0
White	Ordinal	Ethnicity dummy variable
Asian	Ordinal	Ethnicity dummy variable
African American	Ordinal	Ethnicity dummy variable
Latino	Ordinal	Ethnicity dummy variable
Native American	Ordinal	Ethnicity dummy variable
Race missing	Ordinal	Ethnicity dummy variable
Age =< 20	Ordinal	Student's age is 20 or younger
Age = 21-26	Ordinal	Student's age is between 21 and 26
Age => 27	Ordinal	Student's age is 27 or older
AGI missing	Ordinal	Adjusted Gross Income is missing
AGI =< \$20736	Ordinal	Adjusted Gross Income is \$20,736 or less
AGI > \$20736	Ordinal	Adjusted Gross Income is more than \$20,736
Independent tax status	Ordinal	Tax status is independent
Dependency tax status missing	Ordinal	Tax status is missing
Dependent status	Ordinal	Tax status is dependent
FAFSA submitted	Categorical	Student submitted a FAFSA
Math score missing	Ordinal	ACT math score is missing
Math score =< 20	Ordinal	ACT math score is 20 or less
Math score > 20	Ordinal	ACT math score is more than 20
Reading score missing	Ordinal	Reading placement test score is missing
Reading score =< 75	Ordinal	Reading placement test score is 75 or less
Reading score = 75.1-90	Ordinal	Reading placement test score is greater than 75 and equal to or less than 90
Reading score > 90	Ordinal	Reading placement test score is greater than 90
No transfer credit	Categorical	Student does not have transfer credit
Student has not received free aid	Categorical	Free aid consists of grants and scholarships

Table 4.1 (continued)

Student does not have drops	Ordinal	Student's record does not show any dropped courses (courses removed from schedules in the first week of the semester)
Student returning with drops	Ordinal	Student has reenrolled and has dropped courses on academic record (courses removed from schedules in the first week of the semester)
New student/no credit last 5 years	Ordinal	Student is new and/or does not have an academic record within last 5 years
Student does not have withdrawals	Ordinal	Student's record does not show any withdrawals from courses (leaving a course after the first week of the semester)
Student returning with withdrawals	Ordinal	Student has reenrolled and has withdrawals from courses on academic record (leaving a course after the first week of the semester)
New student/returning after 5 years	Ordinal	Student is new and/or does not have an academic record for the last 5 years
No GPA yet	Ordinal	Student is new and does not have an academic record
GPA ≤ 2.77	Ordinal	Student's cumulative GPA is equal to or less than 2.77
GPA = 2.78-3.44	Ordinal	Student's cumulative GPA is equal to or between 2.78 and 3.44
GPA > 3.44	Ordinal	Student's cumulative GPA is more than 3.44
If returning student, all past courses passed	Categorical	Students has reenrolled and earned a grade of C or higher in all previous courses
Taking < 6 credits	Ordinal	Student is enrolled in less than 6 credit hours
Taking 6-9 credits	Ordinal	Student is enrolled in between 6 and 9 credit hours
Taking 10-11 credits	Ordinal	Student is enrolled in between 10 and 11 credit hours
Taking > 12 credits	Ordinal	Student is enrolled in 12 or more credit hours
No developmental math score	Ordinal	Math placement test score average is missing
Developmental math score ≤ 6	Ordinal	Math placement test score average is equal to or less than 6
Developmental math score = 6.1-7.67	Ordinal	Math placement test score average is greater than 6 and equal to or less than 7.67
Developmental math score > 7.67	Ordinal	Math placement test score average is greater than 7.67

Table 4.1 (continued)

Student not receiving free aid	Ordinal	Student is not receiving grants or scholarships this term
Student receiving <\$5729	Ordinal	Student received less than \$5,729 in grants and scholarships this term
Student receiving =>\$5729	Ordinal	Student received equal to or more than \$5,729 in grants and scholarships this term
Student did not received Pell	Categorical	Received Pell Grant = 1, did not receive Pell Grant = 0
%High-difficulty courses	Ordinal	Percentage of student's courses categorized as high-difficulty
%High/moderate-difficulty courses	Ordinal	Percentage of student's courses categorized as high-to-moderate difficulty
%Moderate/low-difficulty courses	Ordinal	Percentage of student's courses categorized as moderate-to-low difficulty
%Low-difficulty courses	Ordinal	Percentage of student's courses categorized as low-difficulty
%Online courses	Categorical	Percentage of student's courses delivered online
%000-level courses	Ordinal	Percentage of student's courses at the 000-level
%100-level courses	Ordinal	Percentage of student's courses at the 100-level
%200-level courses	Ordinal	Percent of student's courses at the 200-level
%Courses retaking	Categorical	Percentage of student's courses the student is retaking

Note. The table provides the list of variables used in the propensity score analyses and in the regression analyses. Dummy variables were created for almost all of the initial 23 variables Aviso stated it used in its algorithms. The 22 row-line divisions of variable groups reflects Aviso's original 23 variables because "%Courses retaking" represents as one variable for this study's models 2 of the 23 that were redundant.

The assumption of common support requires that the propensity-score distribution for the participant and nonparticipant groups overlaps enough to allow for further analysis (Caliendo & Kopeinig, 2008; and Khandker et al., 2010). The regression analyses of the data in this study were conducted using only the overlapping observations described later in the propensity score analysis section.

Institutional Context and Population

The setting for this research study was a southeastern community college serving multiple rural counties with agricultural- and industrial-based economies. The college has an open-admissions policy; the only requirement for college-curriculum admissions is a high school diploma or high-school-equivalent certification (e.g., passing scores in each subject area of the GED test). At the time of this study, the college offered two university-transfer associate degrees and numerous career-and-technical associate of applied science degrees and related diplomas and certificates. The general characteristics of the college's students vary among curriculum programs, but the descriptive statistics for the student population as a whole indicate that 45% of students are full-time; 64% are female; 58% are white; 23% are African American; 13% are Hispanic; 54% are 24 years old or younger; and 60% received some type of financial aid (National Center for Education Statistics, 2015).

Participants

The participant sample groups consisted of students enrolled in curriculum programs as credential-seeking students during the Fall 2015 semester (N=4,521). Aviso collected data on all of these students before and during the Fall 2015 semester. Of the credential-seeking student population enrolled in the Fall 2015 semester, 772 were identified as low-performing/red students; 1,224 were identified as moderate-performing/yellow students; and 2,525 were identified as high-performing/green students.

Assignment to Groups

Predicting propensity for selection into treatment using the full dataset would have made little sense, as the effects of the covariates would be in the opposite direction for green and red students. To establish appropriate comparison groups, two sample datasets were created from the full dataset of green, yellow, and red students. One sample included only green and yellow students, and the other sample included only yellow and red students. Dividing the full dataset in this manner allowed for the testing of two types of treatment groups: untreated green versus treated yellow students, and treated yellow versus untreated red students. The green-yellow sample initially contained 3,749 observations, and the yellow-red sample initially contained 1,996 observations. The procedures for the propensity score analyses and subsequent inverse probability of treatment weighting for each sample were the same.

Variables

This study contained three types of variables: treatment, matching covariates, and outcomes. Each type is described below.

Treatment Variable

The treatment variable for this study was being flagged yellow at the student-level profile in the Aviso platform. This variable was dichotomous: students were either flagged as yellow or not flagged as yellow at the student-level. The treatment under investigation in this study was the student-success coaches' offer of proactive coordinated and individualized support services to the students flagged as yellow. Acceptance of the student-success

coaching services was voluntary, though it is important to note that recent research has indicated that the coach-initiated contact could have an effect on student success even if students did not accept the offered support service (Bettinger & Baker, 2014; Castleman & Page, 2015; Castleman & Page, 2016; and Ideas42, 2016; and Richie & Hargrove, 2005). However, the amount of contact and/or assistance students received from student-success coaches was not collected and, therefore, was not available in the Aviso data warehouse from which this study's data came.

Matching Covariates

For this study, the matching covariates included variables such as age; gender; race/ethnicity; adjusted gross income; financial aid status; dependency status; placement test and/or standardized test scores; course load; course level; and course withdrawal history. In addition to the matching covariates already in the data, I created for each student an average of predicted grades variable to use in the propensity score analysis (and later regression analyses). While I had access to all the data for the variables from the community college in this study, I did not have access to the observations from its peer institutions that were also used in Aviso's predictive analytics for students at the community college of this study. Because the peer-institution data used for predicting student performance were inaccessible, using the average of predicted grades for each student facilitated making the groups more comparable than they would have been without the average.

Outcome Variables

As with the matching covariates, the outcome variables—semester GPA and semester-to-semester persistence—are consistent with the typical outcomes measured to evaluate the impact of interventions designed to improve student success (Bettinger & Baker, 2014; Boden, 2011; Cabrera et al., 1993; David et al., 2013; and Schnell & Doetkott, 2003). This study specifically investigated the outcomes of student GPAs for Fall 2015 and student persistence from Fall 2015 to Spring 2016. To measure these outcomes, I generated two new variables in the data. I created a Fall 2015 semester GPA variable for each student using the course grades each student earned, corresponding quality points, and credit hours. I also created a fall-to-spring persistence variable using spring enrollment information already present in the data. Both of the semester GPA and fall-to-spring persistence outcome variables were used to operationalize student integration into the academic systems of the college.

Data Collection

With permission of the community college and Aviso, I collected the data for this study from Aviso. Aviso collected its data from the college's institutional records system and the college's learning management system, Blackboard. Using these data sources, Aviso also generated its own observations when predicting course grades for each course in which students were enrolled and then flagging courses and students according to those predictions.

The data from Aviso included all of the variables Aviso used in its predictive analytic models as well as the grades students actually earned in each course and whether students

were enrolled in the Spring 2016 semester. Participant privacy and information security were protected because Aviso anonymized the data set, which was stored in accordance to approved procedures outlined in the North Carolina State University's Institutional Review Board application.

Propensity Score Analysis

Propensity score analysis of the data occurred in several steps. First, a propensity score model was developed and used to calculate propensities for being flagged yellow. Then the datasets were trimmed to include only the observations that fell within the propensity score overlaps of each sample. Following trimming, weights for the inverse probability of being flagged yellow were assigned to the units of observations in each sample, and, finally, the variable balances between each group in each sample were checked. The following sections outline in detail these procedures.

Propensity Score Model and Calculations

I estimated the propensity of students to be flagged yellow using derivatives of 22 of the 23 variables Aviso used to predict course grades. Due to collinearity with the *Dependency tax status missing* variable, the *FAFSA submitted* variable was excluded from the propensity score and later analyses. I created dummy variables for most of Aviso's remaining 22 original variables. I also created an average predicted course grade for each student by simply averaging predicted grades for each student. After the variables were created, the propensity score model contained 45 variables—7 dichotomous variables, 36

dummy variables, the average of predicted grades variable, and the squared term of the average of predicted grades variable. The final model for calculating propensity scores was

$$\text{logit} (FLAGGED-YELLOW = 1) = B_0 + B_1(X_i) + B_2(X_i) + \dots B_k(X_{ki})$$

In this model, the B coefficients represent the effects of matching covariates for the value i of each student. The outcome variable is the probability of a student being flagged as yellow—that is, the propensity for being selected into treatment.

The propensity score model was applied to both the green-yellow sample and the yellow-red sample datasets. Table 4.2 displays the model results for the green-yellow sample.

Table 4.2

Propensity Analysis Model for Green and Yellow Student Sample

Variable	Coefficient	SE
Intercept	459.26***	69.78
Aviso average model score	-938.68***	156.05
Aviso average model score squared	469.49***	87.15
Female	-0.61**	0.19
Asian	0.28	0.82
African American	-0.02	0.26
Latino	-0.74**	0.23
Native American	0.26	0.92
Race missing	0.12	0.37
Age = 21-26	-0.62*	0.28
Age => 27	-1.02**	0.35
AGI missing	0.07	0.37
AGI > \$20736	0.63**	0.24
Independent tax status	0.31	0.31
Dependency tax status missing	0.11	0.43
Math score missing	-0.37	0.27
Math score > 20	0.13	0.37
Reading placement score missing	-0.37	0.31
Reading placement score = 75.1-90	-0.07	0.34
Reading placement score > 90	-0.29	0.41

Table 4.2 (continued)

No transfer credit	0.13	0.32
Previously received free aid	0.17	0.33
Returning student with dropped courses	0.15	0.27
New student/no credit last 5 years	0.10	1.06
Returning student with withdrawals	0.79**	0.30
New student/returning after 5 years	1.20	0.85
No GPA yet	0.36	0.32
GPA = 2.78-3.44	0.19	0.28
GPA > 3.44	-0.53	0.45
If returning student, all past courses passed	-0.32	0.31
Taking 6-9 credits	2.35***	0.28
Taking 10-11 credits	3.32***	0.42
Taking > 12 credits	4.52***	0.37
No developmental math score	-0.08	0.33
Developmental math score = 6.1-7.67	0.16	0.40
Developmental math score > 7.67	0.21	0.41
Student not receiving free aid	-0.45	0.52
Student receiving free aid => \$5729	0.31	0.32
Student did not received Pell	0.43	0.54
%High-risk courses	12.60***	2.43
%High/moderate-risk courses	2.17***	0.58
%Moderate/low-risk courses	-0.43	0.30
%Online courses	1.02***	0.25
%000-level courses	1.48*	0.61
%200-level courses	0.32	0.34
%Courses retaking	-0.66	0.54
Prob > chi2	0.000	
Pseudo R2	0.7653	
N	3749	

Note. * = $p < .05$ ** = $p < .01$ *** = $p < .001$.

Table 4.2 indicates that considering the matching covariates, the average of predicted grades was a significant variable in the probability of students being flagged as yellow in the green-yellow sample. In all, there were 16 variables found to be significant in the propensity score model when applied to the green-yellow sample.

Table 4.3 displays the model results for the yellow-red sample.

Table 4.3

Propensity Analysis Model for Yellow-Red Student Sample

Variable	Coefficient	SE
Intercept	-105.26***	20.77
Aviso average model score	221.65***	52.58
Aviso average model score squared	-107.74**	33.07
Female	-0.30	0.24
Asian	0.31	1.16
African American	-0.24	0.28
Latino	-0.32	0.30
Native American	2.45	2.20
Race missing	-0.26	0.49
Age = 21-26	0.05	0.32
Age => 27	0.68	0.45
AGI missing	0.94*	0.39
AGI > \$20736	0.27	0.29
Independent tax status	-0.58	0.36
Dependency tax status missing	-0.62	0.47
Math score missing	0.13	0.33
Math score > 20	0.52	0.57
Reading placement score missing	-0.66*	0.33
Reading placement score = 75.1-90	0.05	0.35
Reading placement score > 90	-0.13	0.47
No transfer credit	-0.09	0.37
Previously received free aid	0.51	0.39
Returning student with dropped courses	0.23	0.28
New student/no credit last 5 years	-2.94*	1.15
Returning student with withdrawals	0.61	0.33
New student/returning after 5 years	-0.65	0.94
No GPA yet	0.85*	0.40
GPA = 2.78-3.44	-0.12	0.37
GPA > 3.44	-0.28	0.79
If returning student, all past courses passed	0.40	0.35
Taking 6-9 credits	-2.79***	0.40
Taking 10-11 credits	-4.25***	0.50
Taking > 12 credits	-4.69***	0.46

Table 4.3 (continued)

No developmental math score	0.15	0.34
Developmental math score = 6.1-7.67	-0.15	0.36
Developmental math score > 7.67	-0.04	0.45
Student not receiving free aid	-0.82	0.74
Student receiving free aid => \$5729	0.43	0.38
Student did not received Pell	1.01	0.76
%High-risk courses	-5.56***	1.20
%High/moderate-risk courses	0.76	0.62
%Moderate/low-risk courses	2.21***	0.43
%Online courses	0.08	0.32
%000-level courses	0.16	0.62
%200-level courses	-1.07*	0.49
%Courses retaking	-0.07	0.51
Prob > chi2	0.000	
Pseudo R2	0.7572	
N	1996	

Note. * = $p < .05$ ** = $p < .01$ *** = $p < .001$

Table 4.3 indicates that considering the matching covariates, the average of predicted grades was a significant variable in the probability of students being flagged as yellow in the yellow-red sample. Similar to the green-yellow sample, 13 variables were found to be significant in the propensity model when applied to the yellow-red sample.

Overlap

I created histograms of the propensity score distributions for each dataset to determine if common support was present in each dataset. Figure 4 displays the pre-trimming propensity-score overlap for the green-yellow sample.

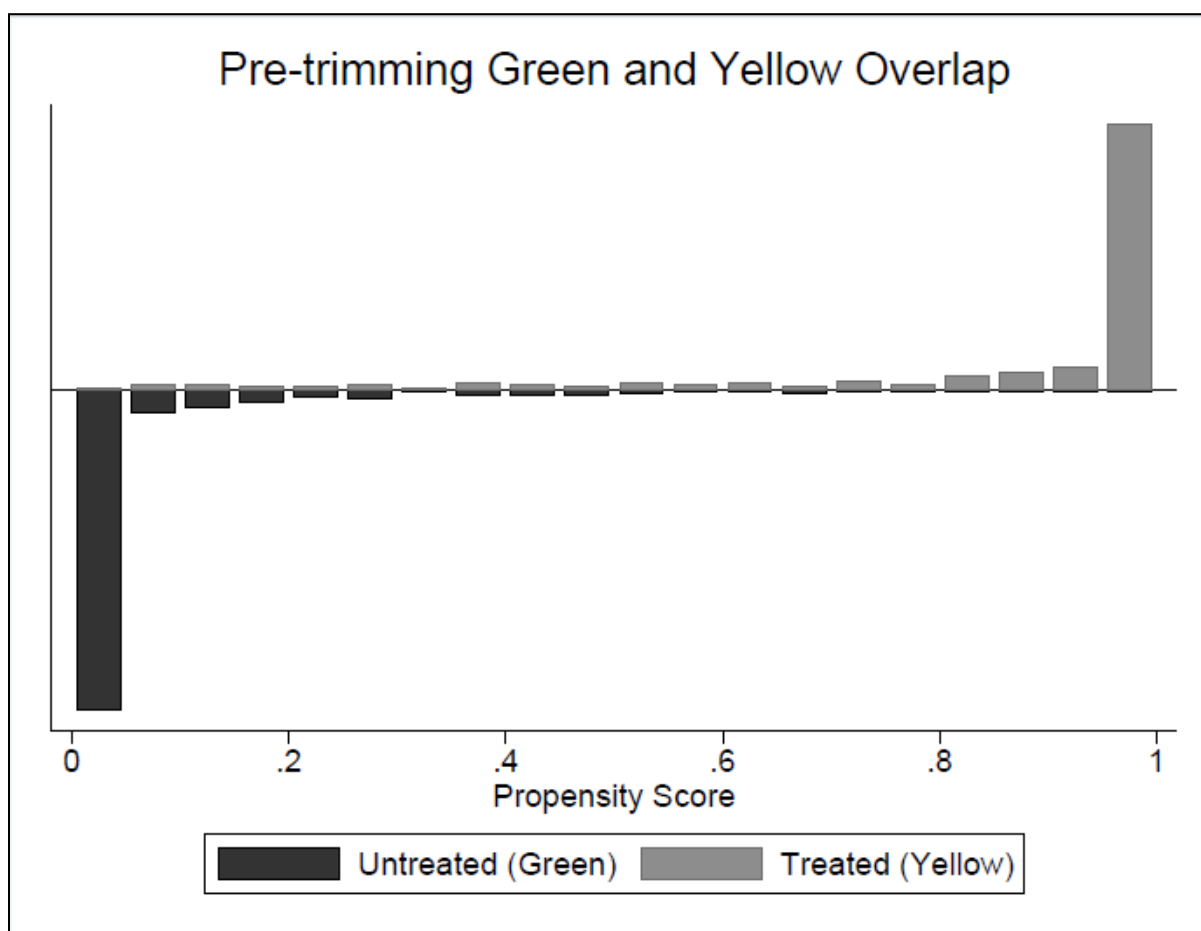


Figure 4. Propensity score overlap for the untreated/green and treated/yellow groups in the green-yellow sample before dropping observations.

Although an overlap of propensity scores within the green-yellow sample was present before trimming the observations, the initial overlap seemed weak as there were many non-overlapping observations close to the scores of 0 and 1. This lack of overlap is not surprising, given that I have all of the covariates that were used to assign students to treatment—with such data the propensity-score model should be highly predictive. To improve the common support, I trimmed the dataset to include only those students who were within the overlap

between the groups by dropping observations with propensities below the maximum of the lowest and minimum of the highest propensity between the groups. The improved overlap between the groups after trimming can be seen in Figure 5.

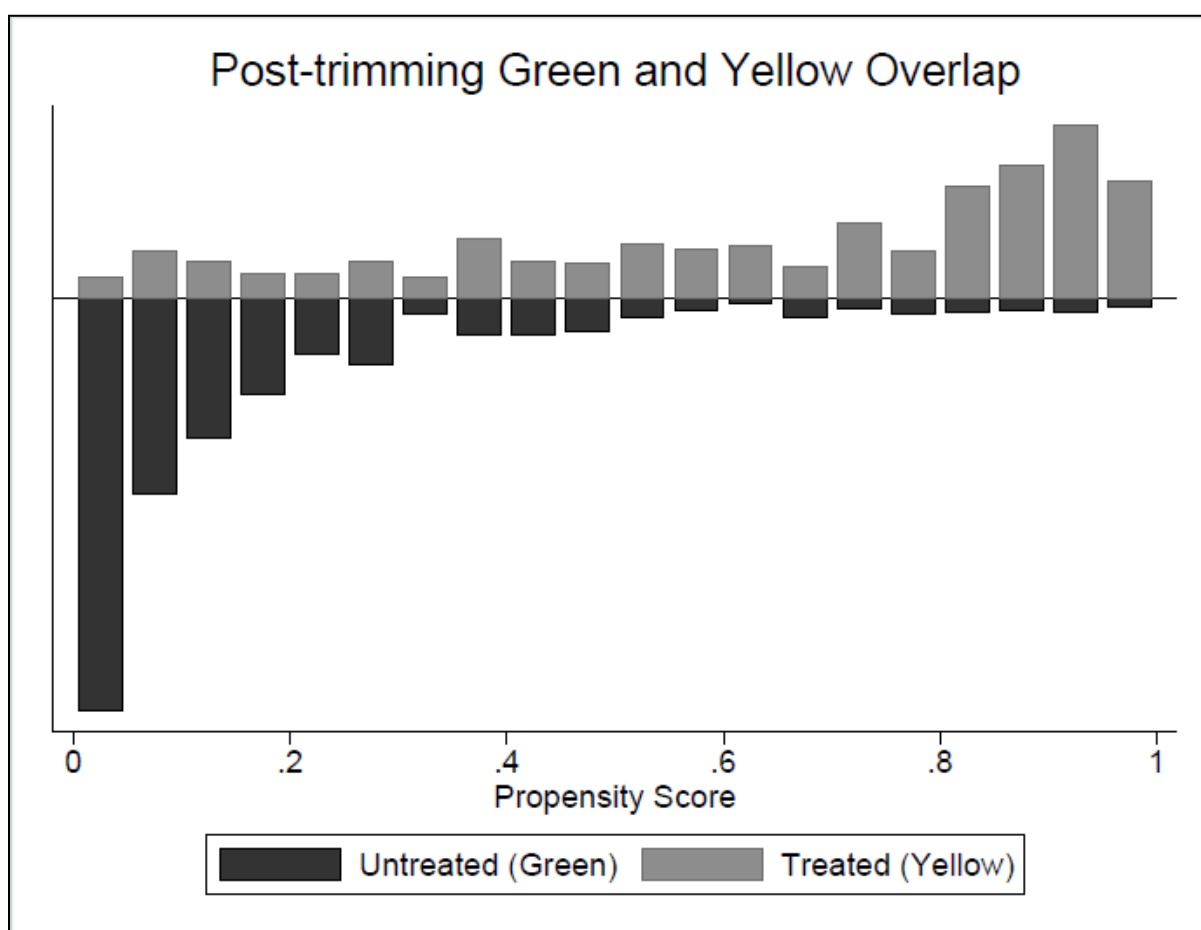


Figure 5. Propensity score overlap for the untreated/green and treated/yellow groups in the green-yellow sample after dropping observations.

As with the green-yellow sample, an overlap of propensity scores for the yellow-red sample was present but weak, with numerous non-overlapping observations as scores approached propensities of 0 and 1. Figure 6 displays the overlap before dropping

observations with propensities below the maximum of the lowest and minimum of the highest propensity between the groups.

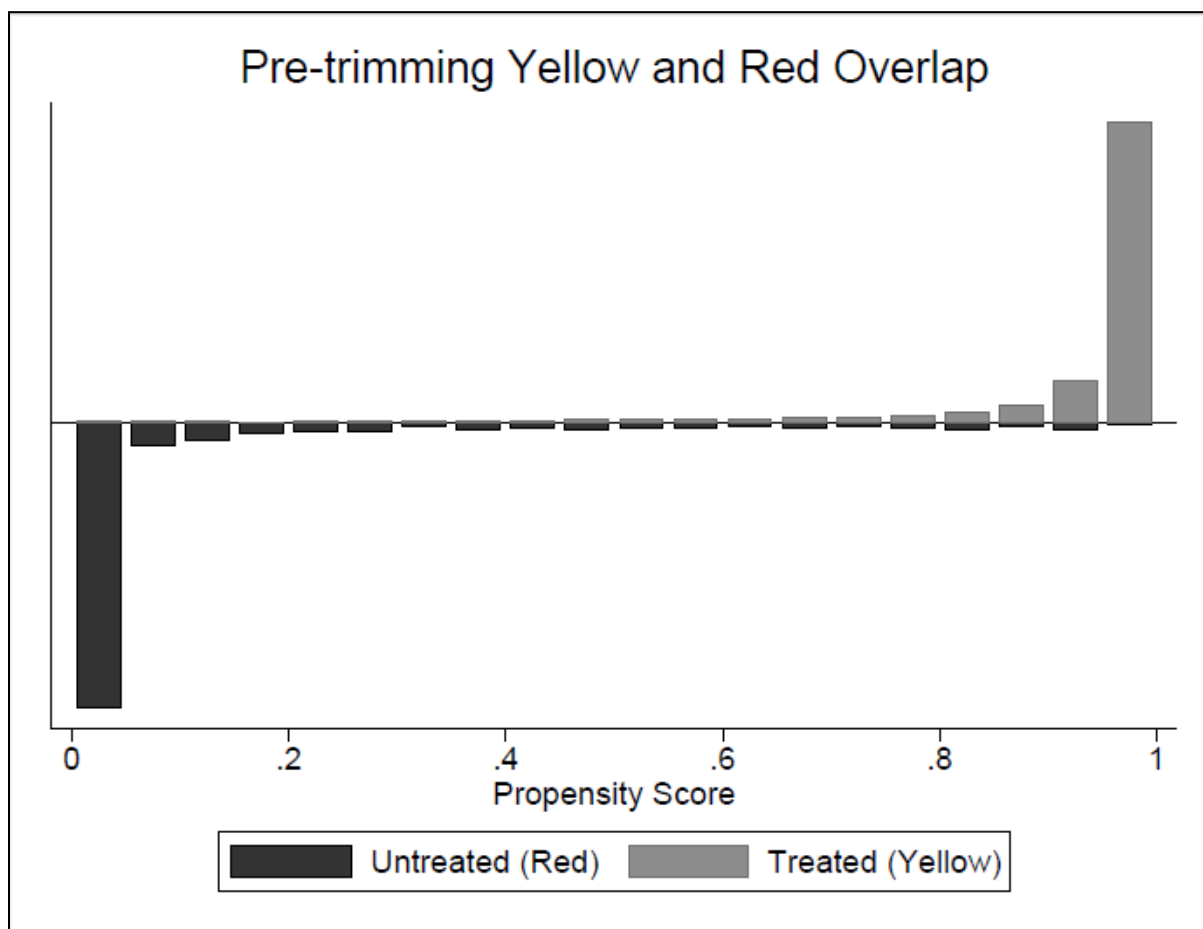


Figure 6. Propensity score overlap for the untreated/red and treated/yellow groups in the yellow-red sample before dropping observations.

Similar to the post-trimming overlap for the green-yellow sample, common support was improved in the yellow-red sample after dropping observations. Figure 7 displays the improved overlap.

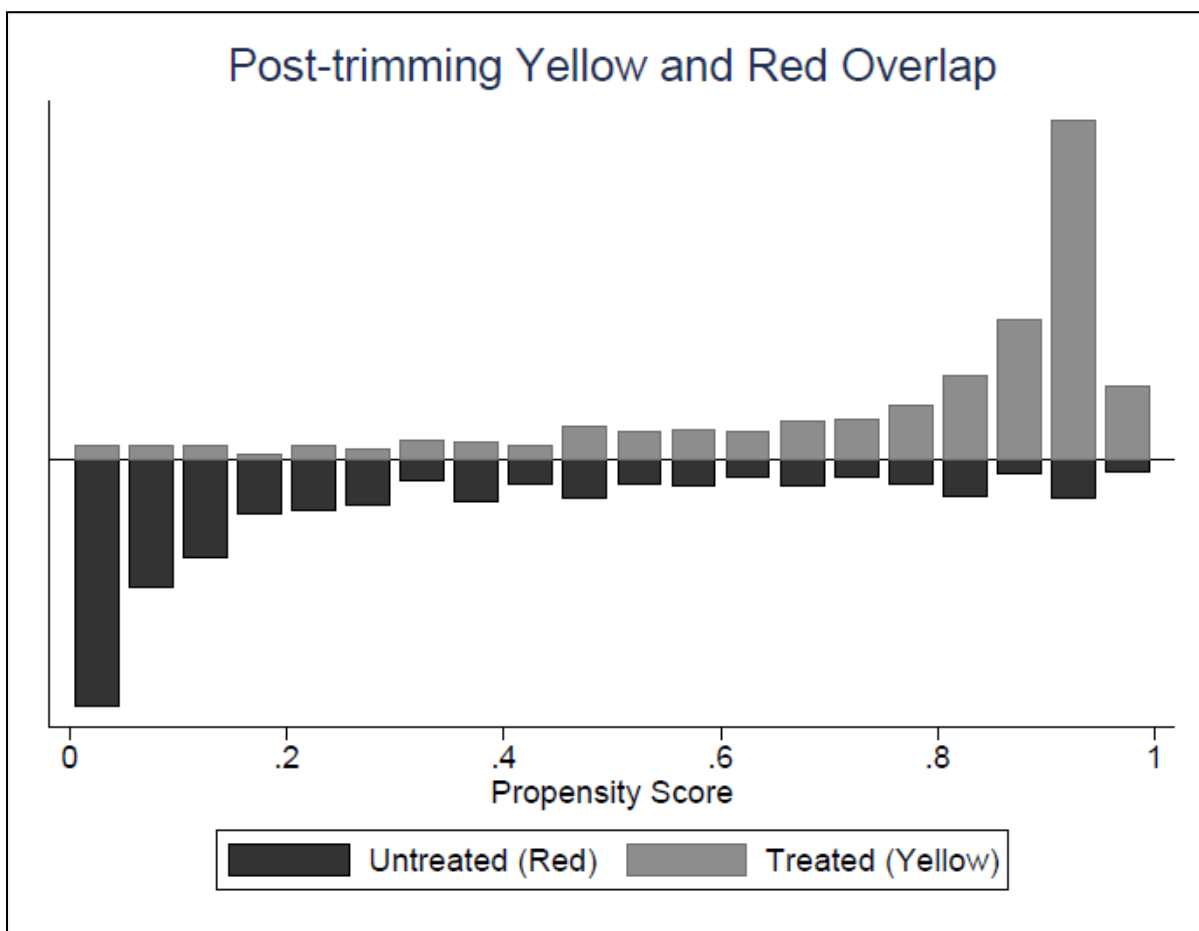


Figure 7. Propensity score overlap for the untreated/red and treated/yellow groups in the yellow-red sample after dropping observations.

The post-trimming overlaps demonstrated that common support was found in each sample. To clarify the number of students removed after dropping the observations that fell outside the overlaps, Table 4.4 provides the number of observations for each group within both samples that were below, in, and above the propensity score distribution overlaps.

Table 4.4

Number of Students below, in, and above the Propensity-Score Overlap

Green-Yellow sample	<i>N</i> students $p < .02$	<i>N</i> overlap	<i>N</i> students $p > .98$	Total N
Green (untreated)	1672	853	0	2525
Yellow (treated)	0	479	745	1224

Yellow-Red sample	<i>N</i> students $p < .01$	<i>N</i> overlap	<i>N</i> student $p > .96$	Total N
Yellow (treated)	0	372	852	1224
Red (untreated)	445	327	0	772

Note: The table presents the numerical distribution of students who were within and outside of the propensity-score overlap for treated and untreated students in each sample. The total number of students is provided in the last column.

As Table 4.4 displays, 853 green and 479 yellow students remained in the green-yellow sample after removing the students who did not fall within the propensity score overlap. The final green-yellow sample size was 1,332. After removing the students who did not fall within the propensity score overlap in the yellow-red sample, 372 yellow and 327 red students remained for a final sample size of 699.

Weighting

To create these comparable groups, I used the inverse probability of treatment weighting technique. Following the trimming, I calculated the inverse probability of treatment weight for each untreated student based on the student's propensity score. However, a weight of 1 was assigned to all yellow/treated students. Since regression analyses would focus on the average treatment effect on the treated (ATT), the weights to be used to balance the groups within each sample and to be used in regression analyses were calculated as

Treated units (yellow students), $w = 1$

Untreated units (green and red students) $w = p / (1 - p)$.

The assignment of these weights to groups in each sample allowed for better balancing of matching covariates within each sample. With this weighting technique, treated units and untreated units were represented as proportionally similar to each other in each sample. Essentially, all treated units were counted as one unit in further analyses and untreated units were counted more or less than one unit depending on untreated units' propensity scores. In the green-yellow sample, the maximum weight assigned to green students was no greater than 5; that is, I changed all green student weights greater than 5 to equal 5. Of the 853 green students, only 27 weights were changed. In the yellow-red sample, I changed all red student weights greater than 10 to equal 10. Of the 327 red students, only 16 weights were changed. These changes in maximum weights for untreated students in each sample enabled better covariate balances in each sample than without the reduction of maximum weights.

Covariate Balancing within Sample Groups

I was able to create comparable groups within each sample by using the inverse probability of treatment weighting technique. While neither sample had perfect covariate balances between groups, the balances overall improved after applying the steps involved in the inverse probability of treatment weighting technique. Table 4.5 displays the covariate balances and biases for the green-yellow sample before and after applying the inverse probability of treatment technique.

Table 4.5

Balance Check for Green-Yellow sample Before and After Weighting

Variables	Before weighting and trimming				After weighting and trimming			
	Treated	Untreated	Difference	Bias	Treated	Untreated	Difference	Bias
Propensity score	0.86	0.07	0.79	385.10%	0.65	0.63	0.02	7.40%
Aviso average model score	0.83	0.93	0.10	-245.30%	0.87	0.88	0.01	-19.90%
Aviso average model score squared	0.69	0.87	0.18	-249.30%	0.76	0.77	0.01	-19.10%
Female	0.55	0.68	0.13	-26.10%	0.59	0.55	0.04	7.80%
White	0.51	0.67	0.16	-32.70%	0.55	0.55	0.00	0.50%
Asian	0.01	0.02	0.01	-7.60%	0.01	0.00	0.01	3.70%
African American	0.25	0.13	0.12	32.30%	0.19	0.23	0.04	-8.80%
Latino	0.18	0.14	0.04	11.50%	0.19	0.16	0.03	7.10%
Native American	0.01	0.01	0.00	-0.20%	0.01	0.00	0.01	4.10%
Race missing	0.04	0.04	0.00	0.10%	0.05	0.05	0.00	-1.60%
Age =< 20	0.61	0.44	0.17	33.60%	0.62	0.51	0.11	21.50%
Age = 21-26	0.21	0.19	0.02	2.80%	0.20	0.26	0.06	-15.50%
Age => 27	0.19	0.37	0.18	-40.20%	0.18	0.23	0.05	-10.90%
AGI missing	0.53	0.49	0.04	6.90%	0.52	0.45	0.07	12.40%
AGI =< \$20736	0.24	0.24	0.00	0.10%	0.23	0.28	0.05	-12.00%
AGI > \$20736	0.23	0.27	0.04	-8.10%	0.26	0.27	0.01	-2.70%
Independent Status	0.27	0.37	0.10	-21.30%	0.28	0.34	0.06	-11.30%
Dependency missing	0.45	0.43	0.02	3.60%	0.45	0.36	0.09	17.70%
Dependent Status	0.28	0.20	0.08	19.00%	0.27	0.31	0.04	-8.30%
Math score missing	0.81	0.81	0.00	-1.80%	0.79	0.83	0.04	-10.50%
Math score =< 20	0.11	0.08	0.03	10.10%	0.11	0.09	0.02	6.80%
Math score > 20	0.08	0.10	0.02	-7.90%	0.10	0.08	0.02	7.20%

Table 4.5 (continued)

Reading score missing	0.64	0.67	0.03	-5.70%	0.68	0.63	0.05	11.50%
Reading score =< 75	0.17	0.08	0.09	27.80%	0.16	0.19	0.03	-10.00%
Reading score = 75.1-90	0.12	0.11	0.01	0.50%	0.10	0.10	0.00	0.60%
Reading score > 90	0.07	0.14	0.07	-22.10%	0.06	0.09	0.03	-8.40%
No transfer credit	0.91	0.81	0.10	28.30%	0.90	0.90	0.00	-0.20%
Student has not received free aid	0.86	0.81	0.05	15.90%	0.87	0.81	0.06	17.20%
Does not have drops	0.80	0.82	0.02	-3.40%	0.84	0.80	0.04	8.00%
Returning with drops	0.19	0.18	0.01	3.50%	0.16	0.19	0.03	-9.30%
New student/no credit last 5 years	0.00	0.00	0.00	-0.40%	0.01	0.00	0.01	5.40%
Does not have withdrawals	0.71	0.82	0.11	-26.80%	0.79	0.71	0.08	18.80%
Returning with withdrawals	0.27	0.17	0.10	24.70%	0.21	0.28	0.07	-19.40%
New student/returning after 5 years	0.01	0.00	0.01	10.60%	0.01	0.01	0.00	1.30%
No GPA yet	0.54	0.42	0.12	25.20%	0.58	0.50	0.08	16.40%
GPA =< 2.77	0.30	0.11	0.19	48.80%	0.23	0.27	0.04	-10.40%
GPA = 2.78-3.44	0.13	0.20	0.07	-18.20%	0.16	0.18	0.02	-7.30%
GPA > 3.44	0.02	0.27	0.25	-75.10%	0.04	0.05	0.01	-5.30%
If returning, passed all past courses	0.75	0.88	0.13	-36.10%	0.80	0.76	0.04	10.80%
Taking < 6 credits	0.29	0.21	0.08	18.90%	0.22	0.13	0.09	23.30%
Taking 6-9 credits	0.32	0.29	0.03	6.50%	0.30	0.29	0.01	2.30%
Taking 10-11 credits	0.07	0.10	0.03	-10.40%	0.07	0.09	0.02	-6.40%
Taking > 12 credits	0.32	0.40	0.08	-17.50%	0.41	0.49	0.08	-17.10%
No math placement score	0.68	0.80	0.12	-26.30%	0.73	0.70	0.03	5.90%
Math placement score =< 6	0.11	0.05	0.06	24.80%	0.09	0.10	0.01	-7.30%
Math placement score = 6.1-7.67	0.12	0.05	0.07	23.90%	0.10	0.11	0.01	-4.70%
Math placement score > 7.67	0.09	0.11	0.02	-5.70%	0.09	0.08	0.01	2.30%

Table 4.5 (continued)

Not receiving free aid	0.63	0.62	0.01	2.40%	0.61	0.54	0.07	14.20%
Free aid < \$5729	0.13	0.13	0.00	0.20%	0.15	0.18	0.03	-9.90%
Free aid => \$5729	0.24	0.25	0.01	-2.80%	0.24	0.28	0.04	-8.20%
Did not received Pell	0.66	0.66	0.00	0.20%	0.63	0.57	0.06	14.50%
%High-risk courses	0.02	0.00	0.02	22.80%	0.00	0.01	0.01	-14.90%
%high/moderate-risk courses	0.10	0.04	0.06	32.40%	0.08	0.09	0.01	-7.80%
%Moderate/low-risk courses	0.66	0.42	0.24	63.10%	0.61	0.53	0.08	24.30%
%Low-risk courses	0.23	0.54	0.31	-83.70%	0.30	0.37	0.07	-19.50%
%Online courses	0.33	0.29	0.04	10.20%	0.31	0.34	0.03	-9.00%
%000-level courses	0.07	0.01	0.06	35.50%	0.04	0.04	0.00	0.00%
%100-level courses	0.80	0.80	0.00	-0.60%	0.81	0.82	0.01	-7.10%
%200-level courses	0.14	0.19	0.05	-19.10%	0.15	0.13	0.02	7.70%
%Courses retaking	0.08	0.06	0.02	13.50%	0.06	0.06	0.00	-0.90%
<i>N</i>	1224	2525			479	853		
Average bias				32.32%				9.74%

As Table 4.5 displays, the average covariate bias for the green-yellow sample was reduced from 32.3% to 9.7%. Before trimming and weighting less than half of the biases were equal to or less than 10%. However, afterwards almost two thirds of the variable biases were reduced to equal to or less than 10%. Important to note is that the difference in the average propensity scores for the green and yellow groups was reduced from .79 percentage points to just .02 percentage points, also resulting in a bias reduction from 385.1% to 7.4%.

Before trimming and weighting observations, less than a third of the covariates in the yellow-red sample had standardized biases lower than 10%. Following trimming and weighting units within the sample, covariate balances between yellow and red students were improved, with 46 of the 60 variable biases found to be equal to or less than 10%. The average covariate bias for the yellow-red sample was reduced from 38.2% to 6.9%. The initial and improved covariate balances between the yellow and red students are presented in Table 4.6.

Table 4.6

Balance Check for Yellow-Red sample Before and After Weighting

Variables	Before weighting and trimming				After weighting and trimming			
	Treated	Untreated	Difference	Bias	Treated	Untreated	Difference	Bias
Propensity score	0.92	0.13	0.79	384.00%	0.76	0.78	0.02	-4.90%
Aviso average model score	0.83	0.66	0.17	191.60%	0.80	0.80	0.00	-5.50%
Aviso average model score squared	0.69	0.44	0.25	211.20%	0.64	0.65	0.01	-5.10%
Female	0.55	0.57	0.02	-3.20%	0.59	0.63	0.04	-6.50%
White	0.51	0.37	0.14	28.00%	0.41	0.47	0.06	-11.80%
Asian	0.01	0.01	0.00	-1.90%	0.01	0.01	0.00	2.30%
African American	0.25	0.38	0.13	-27.00%	0.32	0.34	0.02	-3.50%
Latino	0.18	0.19	0.01	-3.00%	0.21	0.16	0.05	14.40%
Native American	0.01	0.01	0.00	1.10%	0.00	0.00	0.00	3.10%
Race missing	0.04	0.05	0.01	-0.60%	0.05	0.03	0.02	6.40%
Age =< 20	0.61	0.52	0.09	16.90%	0.53	0.47	0.06	11.40%
Age = 21-26	0.21	0.27	0.06	-15.20%	0.26	0.27	0.01	-2.60%
Age => 27	0.19	0.21	0.02	-4.80%	0.22	0.26	0.04	-11.10%
AGI missing	0.53	0.35	0.18	35.60%	0.40	0.42	0.02	-3.30%
AGI =< \$20736	0.24	0.36	0.12	-25.80%	0.33	0.32	0.01	1.50%
AGI > \$20736	0.23	0.29	0.06	-12.90%	0.27	0.26	0.01	2.10%
Independent Status	0.27	0.36	0.09	-19.70%	0.33	0.35	0.02	-4.20%
Dependency missing	0.45	0.21	0.24	53.70%	0.30	0.27	0.03	6.70%
Dependent Status	0.28	0.43	0.15	-32.20%	0.37	0.38	0.01	-2.10%
Math score missing	0.81	0.83	0.02	-5.20%	0.80	0.77	0.03	7.60%
Math score =< 20	0.11	0.14	0.03	-9.00%	0.15	0.17	0.02	-6.70%
Math score > 20	0.08	0.03	0.05	22.20%	0.05	0.06	0.01	-3.00%

Table 4.6 (continued)

Reading score missing	0.64	0.44	0.20	41.00%	0.51	0.44	0.07	14.30%
Reading score =< 75	0.17	0.35	0.18	-39.90%	0.25	0.29	0.04	-8.10%
Reading score = 75.1-90	0.12	0.15	0.03	-9.30%	0.16	0.20	0.04	-9.80%
Reading score > 90	0.07	0.07	0.00	1.00%	0.08	0.08	0.00	0.10%
No transfer credit	0.91	0.90	0.01	2.20%	0.89	0.88	0.01	1.90%
Student has not received free aid	0.86	0.85	0.01	4.90%	0.83	0.81	0.02	3.20%
Does not have drops	0.80	0.66	0.14	32.80%	0.70	0.66	0.04	8.60%
Returning with drops	0.19	0.33	0.14	-31.70%	0.28	0.33	0.05	-10.60%
New student/no credit last 5 years	0.00	0.01	0.01	-7.40%	0.01	0.00	0.01	8.80%
Does not have withdrawals	0.71	0.51	0.20	43.40%	0.60	0.57	0.03	5.90%
Returning with withdrawals	0.27	0.48	0.21	-42.90%	0.39	0.43	0.04	-8.10%
New/returning after 5 years	0.01	0.02	0.01	-3.40%	0.01	0.00	0.01	8.60%
No GPA yet	0.54	0.32	0.22	46.50%	0.34	0.33	0.01	2.00%
GPA =< 2.77	0.30	0.58	0.28	-57.50%	0.51	0.54	0.03	-5.30%
GPA = 2.78-3.44	0.13	0.09	0.04	14.20%	0.13	0.11	0.02	4.90%
GPA > 3.44	0.02	0.02	0.00	4.30%	0.02	0.02	0.00	0.60%
If returning, passed all past courses	0.75	0.50	0.25	51.90%	0.57	0.57	0.00	-0.80%
Taking < 6 credits	0.29	0.23	0.06	14.70%	0.16	0.15	0.01	1.80%
Taking 6-9 credits	0.32	0.30	0.02	5.90%	0.27	0.33	0.06	-15.00%
Taking 10-11 credits	0.07	0.11	0.04	-15.20%	0.12	0.11	0.01	1.50%
Taking > 12 credits	0.32	0.36	0.04	-10.30%	0.46	0.40	0.06	11.20%
No math placement score	0.68	0.39	0.29	60.90%	0.55	0.54	0.01	2.30%
Math placement score =< 6	0.11	0.37	0.26	-63.90%	0.18	0.15	0.03	7.80%
Math placement score = 6.1-7.67	0.12	0.19	0.07	-19.50%	0.17	0.23	0.06	-14.20%
Math placement score > 7.67	0.09	0.05	0.04	15.40%	0.10	0.09	0.01	4.20%

Table 4.6 (continued)

Not receiving free aid	0.63	0.44	0.19	38.70%	0.54	0.53	0.01	1.10%
Free aid < \$5729	0.13	0.20	0.07	-19.30%	0.16	0.14	0.02	6.80%
Free aid => \$5729	0.24	0.36	0.12	-26.10%	0.30	0.33	0.03	-6.70%
Did not received Pell	0.66	0.46	0.20	40.00%	0.56	0.55	0.01	1.90%
%High-risk courses	0.02	0.22	0.20	-95.00%	0.04	0.09	0.05	-25.60%
%high/moderate-risk courses	0.10	0.13	0.03	-16.70%	0.12	0.11	0.01	5.60%
%Moderate/low-risk courses	0.66	0.43	0.23	65.90%	0.54	0.47	0.07	20.20%
%Low-risk courses	0.23	0.21	0.02	6.00%	0.30	0.34	0.04	-12.80%
%Online courses	0.33	0.38	0.05	-13.50%	0.37	0.35	0.02	3.70%
%000-level courses	0.07	0.35	0.28	-98.40%	0.12	0.17	0.05	-19.40%
%100-level courses	0.80	0.54	0.26	77.70%	0.72	0.70	0.02	5.70%
%200-level courses	0.14	0.11	0.03	13.10%	0.16	0.13	0.03	13.80%
%Courses retaking	0.08	0.17	0.09	-33.80%	0.12	0.13	0.01	-6.00%
<i>N</i>	1224	772			372	327		
Average				38.15%				6.91%

As with the green-yellow sample, using the inverse probability of treatment weighting technique allowed me to produce comparable groups within the yellow-red sample. In particular, the difference in the average propensity scores for yellow and red students was reduced from .79 percentage points to just .02 percentage points. The change in percentage points differences was reflected in the decrease in bias from 384% to -4.9% for this variable.

Empirical Regression Models

After acceptable covariate balances in each sample were achieved, several regression analyses were performed to address the primary questions of this study: compared to other students, what was the effect of offering proactive student-success coaching on the semester GPAs of yellow-flagged students, and what was the effect of the proactive intervention on the fall-to-spring persistence of yellow-flagged students?

Fall 2015 GPA Model

To answer the question regarding academic performance, multiple regression analyses were applied to each sample, with weights and while controlling for covariates, to estimate the potential effects of proactive student-success coaching on students' semester GPA. Since GPA is a continuous variable, multiple regression analyses were appropriate for estimating changes to GPA resulting from the treatment (Cohen, Cohen, West, & Aiken, 2003). The basic equation for the multiple regression was

$$\hat{Y} = B_0 + D_1X_1 + B_2X_2 + \cdots B_kX_k$$

In this equation, \hat{Y} was the estimated semester GPA predicted from the treatment variable D_1 and the covariates X_2 through X_k (see Table 4.1); B_0 is the estimated intercept for the model.

Fall-to-Spring Persistence Model

To answer research question one concerning student persistence from the fall to spring semesters, logistic regressions were applied to each sample, with the weights and while controlling for covariates, to estimate the probability of students re-enrolling in the spring 2016 semester after being offered proactive student-success coaching. The basic equation for the logistic regression was

$$\ln\left(\frac{\hat{P}}{1-\hat{P}}\right) = (B_0 + D_1X_1 + B_2X_2 + \cdots B_kX_k)$$

For this study, the \hat{P} represented the predicted probability that a student would persist from semester to semester, B_0 is the estimated intercept for the model, D_1 was the treatment variable, and X_2 through X_k were the covariates found in Table 4.1.

Although the regression equations to estimate the impact of the intervention on semester GPA and fall-to-spring persistence were different, the covariates on the right side of the equation were the same for the whole-sample analyses. Specifically, D_1 was the treatment variable reflecting whether a student was flagged yellow or not flagged yellow, and X_2 through X_k were the matching covariates used to generate propensity scores and weights. After creating comparable groups for each sample with the inverse probability of treatment weighting technique, I was able to use the weights in these regression models, while controlling for covariates, to take into account remaining differences between treatment and control groups.

CHAPTER 5: RESULTS

The purpose of this study was to estimate the effects of proactive student-success coaching on semester GPA and fall-to-spring persistence. Although the inverse probability of treatment weighting method created comparable groups within each sample, regression analyses with weighted observations were used to address any remaining concerns about covariate balance and conditional independence. I used multiple regression models to estimate treatment effects on semester GPA and logit models to estimate treatment effects on fall-to-spring persistence.

The results for this study are organized by sample group. The results for the green-yellow student sample and subgroups analyses are reported first, followed by the presentation of the results for the yellow-red student sample and subgroups. I examined 10 paired subgroups in each sample for statistically significant treatment effects for students offered student-success coaching. The subgroups included students who were either pursuing or not pursuing a university transfer degree; earning or not earning an associate degree; enrolled in 50% or more or enrolled in less than 50% online courses; new or returning; and female or male. These subgroups were chosen because they represent student groups that presumably would have varied experiences in the community college's academic system. For example, students pursuing a university transfer degree likely have different academic intentions and commitments than students pursuing associate degrees in applied science programs, such as automotive restoration or industrial systems technology. Moreover, the various types of students certainly have varying classroom experiences—most applied sciences programs

have hands-on skills-based curricula whereas university transfer degree students do not (outside of science labs). Similarly, students who experience most of their courses online likely do not come to the college's campuses or sites as often as do their mostly seated counterparts, so their academic experiences are probably unlike those of students who mostly enrolled in seated courses. Furthermore, the asynchronous nature of purely online courses provides an academic experience that is fundamentally different than the real-time in-person experience of seated courses, which would differentiate the academic experiences of students enrolled in 50% or more online courses from students enrolled in less than 50% online courses.

The subgroups were the same for each sample, except for one criterion modification for the logit analysis of the yellow-red subgroup for enrolled online course percentage. The criterion for the percentage of online courses was decreased from 50% to 20% for the yellow-red sample to resolve sample size issues in the logit analysis. Each subgroup model applied weights and controlled for all covariates, except when a covariate was the variable being used to limit the sample to the subgroup. For example, the models for female and male students did not use the variable *Female* that was used in the models for the whole sample analyses because the subgroup analyses were limited to either only females or only males within each sample.

For some subgroups, a few similar variables within the original set of covariates were combined to resolve issues with collinearity. Examining the data for the source of the collinearity issues revealed that the issues were due to very few observations within a

subgroup for the replaced covariate. For example, the observations for some ethnicity variables, like *Asian*, were so few in some subgroups that collinearity could not be avoided. To resolve the issues with the ethnicity variables, I used combined race-category variables already present in the dataset: *Race Category 1* (African American), *Race Category 2* (Hispanic), and *Race Category 3* (not African American or Hispanic). Finally, in the new and returning student models, several variables that were related to previous academic performance were excluded since new students would not yet have academic records. These combinations and exclusions are explained in the appropriate sections below.

While analyses of each whole sample did not yield any statistically significant treatment effects when observations were weighted and while controlling for covariates, a couple of subgroup models for the green-yellow sample did have statistically significant effects.

Green-Yellow Sample Semester GPA

The effects of student-success coaching on the semester GPA were first estimated unweighted and without covariates, then weighted but without covariates, and weighted with covariates. The weighted with covariates regression model used the same covariates as used in the propensity score analyses discussed in the previous chapter. Table 5.1 displays the summary semester GPA regression results for the unweighted, weighted, and weighted with covariates models. The full results for these semester GPA regression models are in Appendix A.

Table 5.1

Green-Yellow Sample GPA Regression Results

Variable	Unweighted	Weighted	Weighted with covariates
Success Coaching	-0.114* (0.057)	0.061 (0.115)	0.084 (0.096)
<i>N</i>	1,332	1,332	1,332
<i>R</i> -squared	0.003	0.001	0.195

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. This table presents only the treatment variable *Success Coaching* and intercept coefficients and standard errors.

Without weighting or controlling for covariates, proactive student-success coaching had a negative significant effect on semester GPA; yellow students on average were estimated to have semester GPAs .11 points lower than green students, significant at $p < .05$. The negative effect was expected for this sample's naïve model since green students were expected to perform better than yellow students. Without weights and covariates, the model should estimate green students to earn higher semester GPAs than would yellow students. However, the weighted model and the weighted-with-covariates model each produced a positive but statistically non-significant effect on semester GPA. The results of the weighted-with-covariates model estimated that the average GPA of the students who were offered proactive student-success coaching (yellow students) was .08 points higher than the average for students not offered the treatment (green students), but the difference was not statistically significant.

Green-Yellow Sample Subgroup Semester GPA Analyses

Of these 10 subgroups, only two subgroup models had statistically significant treatment effects on semester GPA when weighted and controlling for covariates: the

subgroup for students enrolled in 50% or more online courses and the subgroup for students pursuing a university transfer degree. The set of covariates for these subgroups were the same as the whole-sample model, except that the variable *%Online courses* was excluded from the 50%-or-more-online-courses subgroup. Table 5.2 displays the summary results for these two subgroups. Appendix B provides the full results for these subgroups.

Table 5.2

Green-Yellow Sample Subgroups Significant GPA Regression Results

Variable	University Transfer	Online Courses=>50%
Success Coaching	0.350* (0.158)	0.358** (0.132)
<i>N</i>	271	425
<i>R-squared</i>	0.5877	0.4479

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. This table presents only the treatment variable *Success Coaching* and intercept coefficients and standard errors.

The treatment effect in both subgroups was positive. The university transfer subgroup model estimated that on average students in the treatment group earned semester GPAs .350 points higher than did similar students not offered treatment, a significant result at $p < .05$. The model for students who were enrolled in 50% or more online courses estimated that on average students who were offered treatment earned semester GPAs .358 points higher than did similar students who were not offered treatment. This result was statistically significant at $p < .01$. The other eight subgroups did not have statistically significant treatment effects on semester GPA.

The regression models for most subgroups did not require substantive changes to the original whole-sample model. The models for the female and male students excluded the

variable *Female*, and the models for new and returning students excluded the variables *Returning student with dropped courses*; *New student/no credit last 5 years*; *Returning student with withdrawals*; *New student/returning after 5 years*; *no GPA yet*; *GPA=2.78-3.44*; *GPA>3.44*; and *If returning student, all past courses passed*. However, when applying the whole-sample covariate model to the models for students earning or not earning associate degrees, collinearity issues occurred. To resolve these issues, I combined *%High-risk* and *%High-moderate risk* into one variable: *%High/high-moderate-risk courses*. I did the same with the variables related to dropping or withdrawing from courses to create *Returning student with no drops or withdrawals* and *New student/returning no credit 5 years*. The semester GPA regression results for each of the subgroups are provided in Appendix B.

Green-Yellow Sample Fall-to-Spring Persistence

As with the weighted-with-covariates GPA regression model, the weighted-with-covariates persistence logit model used the same covariates as used in the propensity score analyses. Table 5.3 displays the summary results for fall-to-spring persistence. The full results for the logit models are in Appendix C.

Table 5.3

Green-Yellow Sample Logit Results for Fall-to-Spring Persistence

Variable	Unweighted	Weighted	Weighted with covariates
Success Coaching	0.013 (0.025)	0.041 (0.042)	0.057 (0.035)
<i>N</i>	1,332	1,332	1,332

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. This table presents only the effect of the treatment variable *Success Coaching* on students' fall-to-spring persistence. The results provided are the percentage points for the probability of students persisting from fall to spring.

While the treatment effects across all three models were positive, none of the models for fall-to-spring persistence yielded statistically significant treatment effects in the green-yellow sample. The effect size did increase as weights and covariates were included in the models. However, all of the effects were small, ranging from the 1.3% increase in the probability for treated (yellow) students to persist from fall to spring compared to students not offered treatment (green) in the unweighted model to the 5.7% increase in probability of persistence in the weighted-with-covariates model.

Green-Yellow Subgroup Fall-to-Spring Persistence Analyses

Of the 10 subgroups, only the models for the students-not-earning-an-associate-degree and for students-enrolled-in-less-than-50%-online-courses subgroups had statistically significant treatment effects. Table 5.4 displays the summary results, and the full results for these subgroup models are in Appendix D.

Table 5.4

Green-Yellow Subgroups Fall-to-Spring Persistence Significant Results

Variable	Not Associate Degree	Online<50
Success Coaching	0.168* (0.073)	0.086* (0.043)
<i>N</i>	482	907

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. This table presents only the effect of the treatment variable *Success Coaching* on students' fall-to-spring persistence. The results provided are the percentage points for the probability of students persisting from fall to spring.

For students who were offered proactive student-success coaching (yellow students) and who were not earning an associate degree, the logit model for this subgroup estimated a 16.8% increase in the probability of those students to persist from fall to spring compared with

similar students who were not offered coaching (green students). This result was significant at $p < .05$. The model for students who were enrolled in less than 50% online courses estimated an 8.6% increase in the probability of students offered treatment to persist compared to students not offered treatment, a significant result at $p < .05$.

Important to note about the above subgroup results is that neither model used the original set of covariates—issues with collinearity occurred in both subgroup models when the whole-sample model was used. To resolve the issues, the models for students earning or not earning an associate degree combined *%High-risk courses and %High/moderate-risk courses* and replaced these original covariates with *%High/high-moderate-risk courses*. Likewise, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

In the models for students enrolled in 50% or more online courses or enrolled in less than 50% online courses also replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals* with *Returning student with drops or withdrawals*, as a combined variable, as well as replaced covariates *New student/no credit last 5 years* and *New student/returning after 5 years* with *New student/returning no credit 5 years*. Furthermore, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino* since the ethnicity dummy variables caused collinearity issues when using the whole-sample model.

Whereas few issues were observed in the semester GPA regression models for the green-yellow sample subgroups, issues were observed in each of the fall-to-spring persistence logit models for the green-yellow sample subgroups when the whole-sample model was used. As with the above discussed subgroups, the models for students who were either pursuing or not pursuing a university transfer degree, new or returning, and female or male also substituted variables similar to the original covariates of the whole-sample model to resolve model issues. The covariate substitutions for the other subgroup models are noted in Appendix D.

Yellow-Red Sample Semester GPA

Table 5.5 displays the summary results for the yellow-red sample semester GPA regression. The full results for the regression models are in Appendix E.

Table 5.5

Yellow-Red Sample Semester GPA Regression Results

Variable	Unweighted	Weighted	Weighted with covariates
Success Coaching	0.277** (0.084)	0.063 (0.145)	0.008 (0.108)
<i>N</i>	699	699	699
<i>R</i> -squared	0.0153	0.0008	0.2489

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. This table presents only the treatment variable *Success Coaching* and intercept coefficients and standard errors.

Similar to the semester GPA regression results for the green-yellow sample, the effect of treatment on semester GPA was statistically significant in the unweighted model. However, unlike the green-yellow sample's unweighted model, the treatment effect was positive in the yellow-red sample's unweighted model. Since red students were not expected to perform as

well as yellow students, the positive treatment effect found for the naïve model without weights and without controlling for covariates was anticipated. The weighted model and the weighted-with-covariates model also had positive treatment effects, but they were not statistically significant. While not statistically significant, the weighted-with-covariates model estimated that the average GPA of students offered proactive student-success coaching (yellow students) was .008 points higher than was the average GPA of students not offered treatment (red students) in this sample.

Yellow-Red Sample Subgroup Semester GPA Analyses

I examined the same 10 subgroups in the yellow-red sample that I investigated in the green-yellow sample. No statistically significant effects of proactive student-success coaching on semester GPA were estimated in any of the yellow-red subgroup models.

Unlike the semester GPA regression models for subgroups in the green-yellow sample, I had to substitute variables for covariates found in the whole-sample analyses in each of the yellow-red sample subgroup regression models to avoid collinearity issues. The covariate substitutions and the full results for the subgroup models are noted in Appendix F.

Yellow-Red Sample Fall-to-Spring Persistence

The summary results for the estimated effects of student-success coaching on fall-to-spring persistence are displayed in Table 5.6. The full results for the fall-to-spring logit models are found in Appendix G.

Table 5.6

Yellow-Red Sample Logit Results for Fall-to-Spring Retention

	Unweighted	Weighted	Weighted with covariates
Success Coaching	0.076* (0.033)	0.014 (0.055)	0.000 (0.039)
<i>N</i>	699	699	699

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. This table presents only the effect of the treatment variable *Success Coaching* on students' fall-to-spring persistence. The results provided are the percentage points for the probability of students persisting from fall to spring.

Although the treatment effects for all three models are positive, only the unweighted model yields a statistically significant effect, at $p < .05$. Unlike the increase in treatment effects found in the green-yellow sample, the treatment effect in the yellow-red sample decreased from .076 in the unweighted model to .014 in the weighted model to .000 in the weighted-with-covariates model. The weighted-with-covariates model estimated a 0% increase in the probability for yellow students proactively offered student-success coaching to persist from fall to spring compared to red students who were not proactively coached. This result was statistically non-significant.

Yellow-Red Sample Subgroup Fall-to-Spring Persistence Analyses

Similar to the semester GPA regression analyses of the 10 subgroups, none of the models for subgroups in the yellow-red sample had statistically significant treatment effects on fall-to-spring persistence.

As was found in the semester GPA regression subgroup models, issues with collinearity occurred when the whole-sample logit model was used for the subgroups. Each subgroup's model was modified to avoid collinearity. However, covariate substitutions did

not resolve the issues that occurred due to the small number of students in the subgroup of students enrolled in less than 50% online courses. To increase the subgroup's size enough to avoid model issues, the paired subgroups' criterion for the percentage of online courses in which students were enrolled was decreased from the 50% used in the subgroups' semester GPA regression models to 20% for the subgroups' logit models. The covariate substitutions and the full results for the subgroup models are noted in Appendix H.

Summary of Results

The overarching hypothesis of this study was that the treatment would have positive and statistically significant effects on student outcomes. Overall, the results do not support the overarching hypothesis. Of the four sample models (2 outcomes x 2 samples) and 40 sample subgroup models (2 outcomes x 2 samples x 10 subgroups) examined, only four models (all subgroups) estimated statistically significant effects of proactive student-success coaching on student outcomes. Additionally, the treatment effects among the models were inconsistent in their directions, and some effects were very small in size. The yellow-red sample analysis for persistence was negative, and 14 of the 40 subgroup models were negative as well. While the sizes of the effects were not hypothesized, the sizes of treatment effects such as the semester GPA coefficient of .008 and persistence odds of -.001 for the yellow-red sample seem negligible. To illustrate the overall patterns found in the models, Table 5.7 displays the summary results for the sample and subgroup models with weights and covariates.

Table 5.7

Summary Results for All Sample and Subgroup Analyses

	Green-Yellow			Yellow-Red		
	Semester GPA	Persistence	<i>N</i>	Semester GPA	Persistence	<i>N</i>
Whole-sample	0.084	0.358	1332	0.008	-0.001	699
Subgroups						
University transfer	0.350*	-0.262	271	0.336	---	186
Not university transfer	0.087	0.064	579	0.025	0.546	414
Associate degree	0.184	-0.169	850	0.175	0.175	600
Not associate degree	-0.006	1.023*	482	---	---	99
Online courses => 50%	0.358**	-0.065	425	0.210	---	285
Online courses < 50%	-0.082	0.589*	907	0.005	---	414
Online courses => 20% ^a	---	---	---	---	0.347	404
Online courses < 20% ^a	---	---	---	---	-0.133	295
New	0.162	-0.048	599	-0.096	-0.031	478
Returning	-0.016	0.378	733	0.176	0.145	221
Female	0.178	-0.093	826	0.140	0.379	420
Male	-0.025	0.906	506	-0.189	-0.635	279

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. ^aDue to collinearity issues with the persistence subgroup model for students enrolled in 50% or more online courses in the yellow-red sample, the percentage of online courses was reduced to 20% for the persistence model in the yellow-red sample to estimate the treatment effects. The other three models that relate to the percentage of online courses did not have the issues with collinearity, so the criteria remained 50%. All results in the table are from models using weights and covariates. Models that had issues with either subgroup size or collinearity are not reported, and their missing results are denoted by three dash marks.

Overall, each of the whole-sample analyses did not yield any statistically significant effects of proactive student-success coaching offered to yellow students when the models used weights and controlled for covariates. Furthermore, only two subgroups in the green-yellow sample had statistically significant treatment effects on semester GPA: students pursuing university transfer degrees and students enrolled in 50% or more online courses. Regarding treatment effects on persistence for green-yellow sample subgroups, statistically significant treatment effects were also only found for two subgroups: students not earning associate degrees and students enrolled in less than 50% online courses. None of the yellow-red sample subgroups had statistically significant treatment effects on either semester GPA or fall-to-spring persistence. In short, save for a few green-yellow sample subgroups, the regression and logit models did not estimate any statistically significant treatment effects.

CHAPTER 6: DISCUSSION AND IMPLICATIONS

As noted in previous chapters, student persistence to graduation is generally low. In particular, 60% of baccalaureate-degree-seeking students graduate within six years of starting postsecondary education, and only 30% of associate-degree-seeking students graduate within three years (National Center for Educational Statistics, 2016). These low graduation rates warrant the examination of interventions and systems designed to improve student outcomes that culminate in graduation, such as semester GPA and semester-to-semester persistence. Such investigation has important implications for all postsecondary institutions and, especially, for the reported 90% of institutions that have been implementing interventions similar to student-success coaching (such as intrusive and/or appreciative advising) that rely on predictive- or early-alert student-monitoring systems as their primary intervention tool (Hanover Research, 2014). Moreover, any empirical research on these practices and tools is valuable because so few studies have used experimental or quasi-experimental methods to estimate treatment effects. To help fill the empirical research gap, this study utilized the inverse probability of treatment weighting method to examine the effects of proactive student-success coaching on outcomes among comparable groups of coached and not coached students.

Specifically, the purpose of this study was to estimate effects of offering proactive student-success coaching on students' semester GPAs and fall-to-spring persistence. Statistically significant treatment effects were found for a few subgroups in the green-yellow sample. However, the results for the rest of the subgroups and, more importantly, for the

whole-sample analyses of both the green-yellow and the yellow-red samples did not indicate that the treatment had statistically significant effects on student outcomes. Overall, this study's results do not support the hypothesis that proactive student-success coaching initiated by the predictive analytics of a student-monitoring system improves student outcomes. While not an affirmation of the intervention or of the use of student-monitoring systems, the results of this quasi-experimental study contribute to the developing literature and limited empirical research on predictive-analytics-informed student-success coaching.

Discussion of Results

Using the methods previously described, appropriately balanced samples of the proactively coached students (yellow) and not proactively coached students (green and red) were created that satisfied the conditional independence and common support assumptions required for quasi-experimental research techniques. In all, 44 models were tested: four whole-sample (2 outcomes x 2 samples) and 40 subgroup models (2 outcomes x 2 samples x 10 subgroups). Of the 40 subgroup models tested, only four models in the green-yellow sample had statistically significant treatment effects.

Implications of Semester GPA Analyses

In the semester GPA regression analyses, two subgroups in the green-yellow sample were estimated to have statistically significant treatment effects on semester GPA: the subgroup of students pursuing a university transfer degree and the subgroup of students enrolled in 50% or more online courses. For both subgroups, proactive student-success coaching was estimated to have about the same positive effect on the semester GPA of

treated students: on average yellow students in each subgroup earned semester GPAs that were .350 and .358 points higher than the GPAs earned by green students, respectively. That the treatment positively affected these student subgroups suggests that the students in the two subgroups might have been more susceptible to low academic performance than were students in other subgroups for which semester GPA analyses estimated null results. That is, there may be aspects of the academic experience for students in these two subgroups that are different enough from the experiences of students in other subgroups to cause variance in the effects of the proactive help student-success coaches offered related to course success.

For example, more students at the college from which this study's data came were enrolled in university transfer degree programs than were enrolled in any one of the numerous applied science programs. Students not enrolled in university transfer programs typically enroll in almost all of the same courses with the same instructors on the same campuses at the same time as the other students in their specific applied sciences curriculum programs. Furthermore, the enrollments for associate of applied science programs vary from as little as 20 to only about 100 students whereas closer to 1,000 students are enrolled in university transfer programs. Essentially, associate of applied science students experience the academic system of the college as small cohorts, and as cohort members the students seem more likely to rely on each other and on their discipline-specific instructors for academic help than to rely on coaches. However, students pursuing university transfer degrees do not experience the college's academic system as a cohort. At the community college, numerous sections of university transfer courses taught by many different instructors are offered at

various times and in various media across the college's entire service area—and sometimes beyond the service area for online-only students. Since university transfer students do not experience the college's academic system as cohort members, they might have fewer opportunities to exchange information beneficial to academic success than do non-university transfer students. In the absence of potential cohort support, the support offered by student-success coaches might have been the assistance that treated university transfer students needed to improve their course performances and, thus, semester GPAs.

Similar to university transfer students, students who were enrolled in 50% or more online courses were less likely to interact with instructors and other students as much as students who were enrolled in less than 50% online courses. Once again, limited time in the seated context and on campus could have limited the opportunity to exchange information. Furthermore, anecdotal observations about students who enroll in 50% or more online courses indicate that such students exhibit these enrollment patterns mostly because they have scheduling conflicts, such as work or child care, or transportation issues that keep them from taking more than 50% of their courses in the seated context. Such challenges also likely influence these students' ability to be academically successful, which is why the proactive student-success coaching might have benefited these students more than it did for students who experience the majority of their courses in a seated context and might not have needed the extra support. Additionally, the type of support coaches provided to students mostly enrolled in online courses might have been different than the type of support coaches offered to students mostly enrolled in seated courses, as some tactics for academic success differ

between seated and online contexts. Different types of support could be more or less effective than other types, yielding mixed results among models.

Implications of Fall-to-Spring Retention Analyses

A statistically significant and positive treatment effect on fall-to-spring persistence was estimated for treated students who were not earning an associate degree. Treated students in this subgroup had a 16.8% increase in the probability that they would persist compared to untreated students in the subgroup. The difference might have been because students in this subgroup were enrolled in either diploma or certificate programs within a curriculum area.

To earn diplomas or certificates in curriculum programs, students are required to complete fewer curriculum courses than are their associate-degree counterparts, and the curriculum courses required for diplomas and certificates are almost all discipline-area-specific courses. For example, students earning the one-year welding certificate will enroll in the same welding-related curriculum courses in which students earning the welding technology associate of applied science degree will enroll. However, the certificate students will not enroll in the non-welding courses, such as freshman composition, in which the degree-seeking students are required to enroll. Fewer requirements translate into fewer courses for which diploma- and certificate-seeking students might have needed to be coached, which might have also resulted in more focused than diluted coaching. Moreover, requiring fewer courses for diplomas and certificates reduces students' time-to-credential and simplifies academic schedules and planning. Since diplomas and certificates are skills-

focused and are only offered in career and technical disciplines, connecting students' short time-to-credential to their employment goals and encouraging students to persist through only one to two semesters was likely easier than doing so for students who needed to persist through at least another two to four semesters of course work to complete an associate degree. Stated otherwise, it might have been easier for a student-success coach to convince a welding-certificate student to enroll in one more semester to earn the credential and then be employed at more than \$20 an hour than it was to convince an Associate Degree in Nursing student to complete the admission prerequisites and then complete another four semesters of coursework to earn the degree and then be employed at or more than \$25 an hour.

The statistically significant estimated positive treatment effect on fall-to-spring persistence for students enrolled in less than 50% online courses seemed contrary to the semester GPA results for this subgroup. While proactive student-success coaching was not estimated to have a statistically significant effect on the average semester GPA for treated students in this subgroup, the subgroup's yellow students were estimated to have on average an 8.6% increase in the probability to persist compared to the subgroup's green students. The seemingly contrary results for this subgroup might have also stemmed from potential differences between how proactive student-success coaching was implemented with students who were on campus for most of their courses and with students who were not on campus as often. That is, maybe treated students who took most of their courses face-to-face had more opportunities than did treated students who took most of their courses online to utilize the college services about which coaches educated them—such as, the financial aid department

and registrar office—that mitigate obstacles to persistence. It might have been easier for student-success coaches to help students with bureaucratic challenges if the students were physically on campus than if the students were not. For example, students mostly enrolled in seated courses might have been led—in-person—to the registrar’s office to resolve an issue whereas students enrolled mostly online might have only been told over the phone or instructed by email that they needed to go to the registrar’s office. Being instructed by phone or email about how to resolve an issue still requires additional actions and overcoming inertia for a student to apply the instructions.

Alternatively, treated students who enrolled in less than 50% online courses might have benefited academically as much or more from in-person interactions with classmates and instructors as they did from interacting with coaches, yielding the null effect on semester GPA for this subgroup. Likewise, treated students who enrolled in 50% or more online courses might have benefited more from their interactions with coaches than they did from their interactions with classmates and instructors, especially since the online interactions with classmates and instructors were likely less frequent than they would have been in a seated context, yielding the statistically significant treatment effect on semester GPAs for students in 50% or more online courses. Finally, the null effects for the fall-to-spring persistence of students enrolled in 50% or more online courses could have resulted from the difficulty in assisting this subgroup to overcome their obstacles to persistence, which are not always the same as the obstacles to course success.

Implications of Potential Inconsistency among Results

The seemingly inconsistent estimates of statistically significant effects among the paired subgroups discussed above—students who were either pursuing or not pursuing a university transfer degree; earning or not earning an associate degree; enrolled in 50% or more or enrolled in less than 50% online courses—indicates that proactive student-success coaching could have affected distinct subgroups of students in the green-yellow sample in different ways. That the other green-yellow subgroups (new, returning, female, and male) and all of the yellow-red subgroups lacked statistically significant estimated treatment effects further signifies that possible effects, if any, vary among subgroups. In short, proactive student-success coaching might affect different subgroups in different ways because students in those subgroups might have different needs and issues. For example, students mostly enrolled in online courses may need student-success coaches to remind them to check course sites often and to make sure to complete assignments before due dates while students mostly enrolled in seated courses do not need those reminders from coaches because their instructors remind them instead. Similarly, because university-transfer students do not have the same by-default cohort experience of associate-of-applied-sciences students, university-transfer students might need the coordination of the academic support services that coaches offer more than do non-university-transfer students. Another explanation for the mixed results, especially when considering the null effects for all of the yellow-red models, is that enough students from all groups inadvertently received forms of the treatment to minimize differences in treatment effects between groups.

Important to note about all of the subgroup analyses is that model specification for each subgroup could also have been the cause of the divergent results. Model specification complicates inferences about the results and their seemingly contradictory trends. Additionally, the sample sizes of subgroups (as well as subgroups within subgroups) and complications with subgroup models limited the statistical power and prohibited further analyses that could have provided insights about the treatment effects. Considering these issues with the subgroup models, the statistically significant treatment effects found in the models for students who were pursuing a university transfer degree, not earning an associate degree, enrolled in 50% or more online courses, or enrolled in less than 50% online courses could have occurred simply by chance even though the results of the models were statistically significant at $p < .05$ or $p < .01$. Consequently, despite the statistically significant treatment effects found for four subgroup models, the null effects of the other 36 subgroup models indicate that the treatment, in general, does not improve outcomes. The statistically non-significant treatment effects estimated for the green-yellow and yellow-red sample analyses corroborate the general ineffectiveness of proactive student-success coaching found in the subgroup analyses.

Of course, all of the above explanations are contingent on the available data and analyses. Given different data, subgroups, and/or analyses, other viable explanations could have also been developed regarding the treatment effects of predictive-analytics-informed student-success coaching. As Gelman and Loken (2013) stated, “A dataset can be analyzed in so many different ways” (p. 1). As the results are, the explanations for the null effects were

constructed after analyses because the null effects were not hypothesized before analyses. If the data had allowed the model specifications for the whole-sample and the subgroup analyses to be exactly the same and the results supported the overarching hypothesis that predictive-analytics-informed student-success coaching improves student outcomes, then, admittedly, the statistically significant treatment effects would have been “taken at face value” and might have been a potential misinterpretation of the data analyses (Gelman & Loken, 2013, p. 5), especially considering the results actually yielded. Since there is a dearth of research about this type of intervention and others similar to it that adequately addressed selection-into-treatment and other threats to validity, the balance in available empirical evidence tilts neither toward nor away from general support for student-success coaching.

Implications of Analyses in the Context of Current Literature

To the date of this dissertation, the literature remains inconclusive regarding the efficacy of proactive student-success coaching. As noted in early chapters, there have been few studies that examined interventions similar to the proactive student-success coaching investigated in this study. In fact, the only study to have specifically estimated the treatment effects of student-success coaching on student persistence while sufficiently resolving selection-into-treatment issues was Bettinger and Baker (2014), which analyzed InsideTrack’s student-success coaching using “quasi-randomly divided lists of students” (p. 7) in covariate-balanced groups. Since Bettinger and Baker (2014) found positive and statistically significant treatment effects for student persistence at 6-, 12-, 18-, and 24-month

periods, the results of the current study challenge to some extent the Bettinger and Baker (2014) findings, albeit with several caveats.

Bettinger and Baker's (2014) research design and analysis techniques were different from those used in this study and could account for the differing findings. However, and likely more important, the dissimilarities in how InsideTrack and the community college implemented student-success coaching could explain more of the variance in results than do the distinctions in the studies' approaches. In particular, the selection-into-treatment process for InsideTrack was fundamentally different from that of the community college. To test the effects of InsideTrack's offer of student-success coaching, Bettinger and Baker (2014) were able to analyze 17 cohorts of coached and not-coached students from various types of postsecondary institutions. The institutions chose the type of cohort for the Bettinger and Baker (2014) study, but those cohorts were not stratified by predicted performance levels like the green, yellow, and red students were at the community college. InsideTrack offered coaching to students randomly assigned (albeit after some manual balancing) to treatment groups within the 17 cohorts. The community college, instead, offered proactive coaching to only the yellow students. Consequently, the estimation of treatment effects in Bettinger and Baker (2014) were based on students of all performance levels within a cohort while this study's estimations were based on differences between similar students at various predicted performance levels. That Bettinger and Baker (2014) found statistically significant treatment effects on student persistence while this study did not suggests the assumption that yellow students might benefit more from student-success coaching than green and red students is

incorrect. Counter to the community college's efforts and expectations, all levels of students might respond in very similar ways to treatment, or below average (red) and above average (green) students might respond to treatment better than average (yellow) students respond. Either way, the prioritization of proactively coaching yellow students could have been misplaced.

The experience and monitoring of InsideTrack's student-success coaches also differentiated InsideTrack's program implementation from the community college's implementation. As discussed in Bettinger and Baker (2014), InsideTrack "has created a large library of tools and resources, and coaches are trained to work with these proprietary methodologies and program to help students" (p. 6-7). InsideTrack also records the calls coaches make to students in order to provide coaches with "extensive feedback on the content and tone of their calls" (p. 7). Bettinger and Baker's (2014) characterization of InsideTrack's coaching operations suggests that InsideTrack's coaches had continuous feedback about their performance and that coaching was their only job responsibility. While Aviso initially trained the community college's coaches and provided professional development to some faculty and other support staff, Aviso was mostly responsible for providing the platform, predictive analytics, and technological support for the proactive student-success coaching offered at the community college. Once the semester started, the community college assumed the responsibility of implementing student-success coaching. The community college student-success coaches met on a regular basis, almost weekly, to discuss implementation and updates, but the degree to which the community college's

coaches were continuously trained and monitored is unknown. The data provided for this study did not include information about the amount of treatment uptake by students or about the degree to which coaches were monitored and provided feedback. Additionally, while the role of student-success coaches at the community college primarily involved coaching students, their responsibilities included activities beyond just contacting students as indicated in Table 3.5 of Chapter 3. Table 6.1 displays some of the similarities and differences between both coaching implementations.

Table 6.1

List of Student-Success Coaching Implementation Features by Organization

Features	Community College	InsideTrack
Predictive analytics	Yes; provided by Aviso.	Yes; internally developed and updated.
Proactive contact	Yes.	Yes.
Continual contact	Yes.	Yes.
Student-service-users	Only students predicted to be moderate performers.	All students randomly selected into treatment.
Number of student-service-users	1,224 out of 4,521 students.	About 6,777 out of 13,555 students in 17 cohorts.
Number of coaches	7	Unspecified.
Responsibilities of coaches	Primarily coaching but also registration and other duties as assigned.	Only coaching.
Professional development for coaches	Yes; initially provided by Aviso, then continued by college administrators and staff.	Yes; continual professional development based on communication monitoring and job performance.
Institution type(s)	Public open-access community college.	Public and private, 2- and 4-year non-profit postsecondary institutions.

Note. The table only represents a reduced list of features and does not constitute a complete list of implementation activities. The community college information came from meeting minutes, and the InsideTrack information came from Bettinger and Baker (2014).

The purpose of Table 6.1 is to highlight the differences between the implementation of student-success coaching offered by different organizations. While both organizations provided proactive student-success coaching, the distinctions between the coaching processes and the target student-users confounds any definitive conclusions about the effectiveness of the intervention. Nonetheless, the differences in the organizations' implementation and in the effects found in Bettinger and Baker (2014) and this study only reinforce the need for more research on student-success coaching.

Possible Issues with the Analyses

There are a few possible reasons why the differences in outcomes for treated and untreated students were not statistically significant: Aviso's predictions were inaccurate, proactive student-success coaching was ineffective or inconsistent, and experimental treatment diffusion occurred.

Aviso's predictions about students' course performance were based on only two years of historical data from the community college and an unknown number of years of historical data from peer institutions (albeit unlikely many years). The amount of historical data could affect the accuracy of the algorithms—maybe more than two years of historical data is required for accurate predictions. Assuming the amount of data was sufficient, the algorithms could still have been inaccurate because they were based on correlations between and among variables, and correlated associations are not causal associations. For example, just because two students are alike in many variables and one of those students dropped a course in the

first semester does not mean that the other student will drop a course the second semester too. Nonetheless, that type of association is the basis for predictions made with analytics. Those associations translate into variable weights within an algorithm, which could be too much or too little when applied to current students. O’Neil (2016) discussed how predictive analytics models need constant refinement and readjustment to remain accurate, but Aviso’s models are only updated each semester, possibly resulting in the inaccurate weighting of variables and, thus, inaccurate predictions. As noted in Table 3.5 of Chapter 3, the course-performance predictions that determined students’ flags were not perfect—the majority of students performed below predictions. This process is temporally different than the predictive-analytics practices used by companies like Google and Amazon—their recommendation analytic models are analyzed and updated almost instantaneously as users search, click, and buy (O’Neil, 2016). In the Aviso platform, students flagged yellow at the start of the semester remained yellow until the start of the next semester—no adjustments were made in the current term for current-term performance.

Building on the possible inaccuracy of the course performance predictions, proactive student-success coaching could have been ineffective because the coaching was informed by the success indicators provided by Aviso’s predictions. Simply stated, if the predictions were wrong, then coaches did not coach the students who needed to be coached. Or, rather, coaches assisted the students who needed to be coached but used inaccurate predictions and success measures to coach the students, resulting in mixed results because the services provided addressed students’ predicted needs not necessarily their actual needs. Assuming

the predictive analytics were accurate, maybe proactively coaching the students predicted to perform the worst—red students—would have had more of an impact on average student outcomes than targeting the yellow students only.

Since faculty and student-support staff were made aware of the intervention before it was implemented, the information about Aviso and student-success coaching might have nudged (Thaler and Sunstein, 2008) faculty and staff to encourage all students to self-initiate support services. While data have not been gathered about these possible faculty nudges, faculty likely encouraged students flagged yellow or red more than they encouraged students flagged green to seek additional academic assistance. If that was the case, faculty and staff could have assumed the role of student-success coaches by default if they encouraged students to seek academic support, which could have reduced the impact of the student-success coaches' proactive assistance in light of others also proactively offering support, especially if others nudged non-treatment students. As Gambino (2017) states about holistic approaches to advising and planning like predictive-analytics-informed student-success coaching, such “whole student” initiatives can “result in increased student success and learning as well as faculty, staff, and institutional learning, leading to transformative institutional change” (p. 68). Additionally, the student support available to all students might have been as effective as the support offered directly by coaches. As noted in the discussion of the treatment in previous chapters, students who came into an academic assistance center and requested help were not denied assistance. Proactive student-success coaching might not have yielded statistically significant differences between yellow students and either green or

red students because the non-yellow students initiated and relied on support services to a degree that reduced the differences between treatment groups to non-significant levels. That is, non-yellow students could have received treatment similar enough to that of yellow students to yield the general non-findings. From this perspective, proactive student-success coaching would have become a supplemental but not essential intervention—affecting students on the margin but not on the whole.

As noted in the discussion of the statistically significant results, proactive student-success coaching could have been ineffective for the whole samples because it is only effective for particular subgroups. Nonetheless, the inconsistency in the results also suggests that the implementation might have been inconsistent. Particular student-success coaches could have been more effective with their caseloads than other coaches were with theirs, which would weaken the strength of the overall treatment effect. Unfortunately, the data provided for this study does not contain information that could provide insights into a coach's effectiveness compared to others. However, if implementation was inconsistent, the lack of implementation fidelity could explain the inconsistent and statistically non-significant results.

Finally, treatment diffusion could have also produced the mixed results across models. Based on the above extrapolations about the subgroups with significant results for semester GPA, yellow students who were in cohorts and/or on campus often could have told green and red students about the help the coaches offered them. That information exchange about support services could have resulted in enough green and red students benefiting from

the coaching the yellow students were offered to influence the results of the sample and subgroup analyses. Since the majority of the students at the college were enrolled in seated courses with cohort members, the transfer of academic advice and information about college services among treated and untreated students was likely, resulting in the null effects for the samples and most subgroups.

Discussion of Predictive Analytics Ethics

Noted throughout this study is that the proactive student-success coaching under investigation was targeted at students predicted to have moderate course performances (i.e., yellow students). Several issues arise from prioritizing support to a subgroup of students, especially when the same predictive analytics indicate that another subgroup of students (i.e., red students) will likely perform worse than the chosen subgroup. Such targeting creates what Lavitt and Carmean (2017) described as the “obligation in the data” (p. 1). Essentially, if coaches, faculty, and support-staff are informed by predictive-alert student-monitoring systems about potential issues that will be detrimental to student outcomes, their obligation to intervene and attempt to help students is increased more than if informed by historical trends. Institutions cannot change the past, but it seems like they should take actions when informed about the future. Even though predictive analytics use historical data to estimate the likelihood of success for current students, predictive analytics inform institutions about current students whom they can help. Since most institutions state that student learning and success (or some variants of this language) are core to their operations, it logically follows

that they would help students they know, or at least anticipate, need help. Not doing so seems like a violation of common educational values.

Biased predictions can confound the obligation(s) in the data. While the accuracy of predictive analytics depends on the algorithmic techniques used to analyze the historical data (Aguilar et al., 2014; Davis & Burgher, 2013; Delen, 2011; Denley, 2014; and Smith et al., 2012), the models that are finally applied to current student data might have embedded bias stemming from the historical data used. As O’Neil (2016) states about college rankings, the algorithms used are “opinions formalized in code” (p. 53), and as such the choice of variables used in the models to predict student performance can vary depending on the stakeholders who are developing the models. That is, as Ekowo and Palmer (2016) stated, “predictive tools can also produce discriminatory results because they include demographic data that can mirror past discrimination included in historical data” (p. 13). The choice of variables and their assigned weight in models can transfer developers’ biases to the models. Since predictive modeling relies on demographic data that “may also unintentionally entrench disparities in college achievement among groups...schools can use algorithms that in the end only pinpoint students who are traditionally ‘at-risk’: underserve populations” (Ekowo & Palmer, 2016, p. 14). Furthermore, because predictive analytics models are almost always companies’ proprietary products, the literature remains unclear about possible biases inherent in models.

The potential biases in predictive tools can create what O’Neil (2016) described as negative feedback loops. In the context of educational settings, the feedback loops could

institutionalize student profiling, especially when the predictive tools are used for enrollment management or course-registration advising. For example, if the historical data trends at an institution correlate success in engineering courses with students' gender and the predictive models use that correlation to inform academic advising, then students might be inadvertently steered away from a discipline in which they might excel. In the case of gender, the trend would have likely been a result of low enrollment of that particular gender subgroup due to historical discrimination, not because of the subgroup's aptitude. If there is a small subgroup within a larger population, it only takes the outcomes of very few members to drastically skew the statistics about that subgroup.

Future Research

While quasi-experimental methods can be acceptable alternatives to the methods used to conduct randomized controlled trials, research that relies on quasi-experimental methods does not meet the gold standard of randomized controlled trials. To date as of this writing, the only study to use experimental methods to estimate the effects of student-success coaching was Bettinger and Baker (2014), albeit with post-randomization modifications. To build on the limited empirical evidence for or against the implementation of predictive-analytics-informed proactive student-success coaching found in Bettinger and Baker (2014) and in this study, more research using at least quasi-experimental designs should be conducted. For even stronger estimates, research that utilizes randomized controlled trails to test treatment effects of proactive student-success coaching would contribute greatly to the information about this type of intervention.

Since student-success coaching seems to be implemented in different ways by various organizations (Google searches yielded over 500 thousand results for “student-success coaches” with no definitive position description), conducting implementation evaluations of student-success coaching programs would also contribute to the literature. Specifically, examining the quality and quantity of coaches’ interactions with students as well as students’ uptake of treatment would provide insights as to why or why not coaching is effective. Such research would reveal the potentially diverse goals, priorities, and activities of stakeholders and coaches alike.

Not unlike implementation evaluations, qualitative studies that explore faculty, coach, student-support staff, and student experiences with student-success coaching might also discover the variables that facilitate or impede the student-success coaching effectiveness. Kalamkarian and Karp (2015) was one of the only studies to explore the student experience regarding what they referred to as technology-mediated advising systems (such as Aviso), but the study was also limited to examining student attitudes about such systems. Since faculty, student-support staff, and coaches are also users of such systems, it is important to understand their experiences as well. Fletcher, Grant, Ramos, and Karp (2016) have also noted these deficits in literature regarding student-success coaching, which they include under a larger category of interventions they have labeled “Integrated Planning and Advising for Student Success (iPASS)” (p. 1) which rely heavily on the technology-mediated advising systems Kalamkarian and Karp (2015) researched. Fletcher, Grant, Ramos, and Karp (2016)

reinforces the literature review in this study as well as makes clear that the limited literature lacks a common language, generally accepted best practices, and empirical evidence.

The above suggestions for future research should also consider the ethical implications of how, why, and when student-success coaching is offered. As noted in the ethics discussion, why institutions chose certain subgroups over other subgroups is an important consideration in understanding the results of any given study. For example, the community college in this study chose to focus predictive-analytics-informed student-success coaching on students who were estimated to have moderate academic performance. The community college chose this subgroup of students because at the time of this study the college had limited resources and decided that targeted coaching would yield the most effective and efficient outcomes. In contrast, the 17 cohorts in Bettinger and Baker (2014) were chosen by the institutions participating in InsideTrack's experiment. As Bettinger and Baker (2014) noted, "each school determined the criteria for inclusion and the size of the sample according to their own priorities...one school [only] assigned athletes" (p. 6). It would seem that the choice of the target audience for student-success coaching would provide important insights into the effectiveness of the intervention as well as whether chosen subgroups should continue being targeted rather than offering proactive student-success coaching to all students.

Limitations

This study had several limitations. Primarily, since the analyses were based on student samples from one public, open-access community college, the generalization of the

results to other student populations is limited. Including more institutions and more types of institutions would help resolve this limitation. Furthermore, because sample and subgroup sizes were limitations that affected regression model specification and caused issues with collinearity among covariates, increasing the sample and subgroup sizes by including more institutions would likely resolve those limitations and improve the statistical power of the regression analyses. Even with the addition of more institutions, other limitations present in this study, such as treatment diffusion and fidelity of implementation, that pose threats to the validity of the results should be mitigated as much as possible. Whereas companies like InsideTrack focus solely on providing student-success coaching to client-institutions and continuously monitor and correct the activities and performance of its coaches, the literature remains unclear about whether other student-success coaching programs manage treatment diffusion and maintain fidelity of implementation.

The study was also limited by the available data. Three types of data could have enhanced the analyses: dosage, treatment tools, and outcomes more distal than one academic year. Regarding treatment dosage, quantitative data for the frequency of coach-and-student meetings; for the number system-generated and coach-resolved alerts; and the ratio of coach-initiated to student-initiated (walk-in) interactions could reveal the levels of exposure various types of students have to the treatment. Related to the treatment dosage, information about the degree to which student-success coaching was standardized, via tools such as email templates and phone-call scripts, could verify the degree of implementation fidelity proactive student-success coaches maintain. Together these areas of data could provide information

about the amount and the type of treatment coaches provided to students. Finally, distal outcomes beyond the semester GPA and fall-to-spring persistence, such as fall-to-fall persistence as well as 100% and 150% graduation rates, could uncover whether or not treatment effects require more time than a semester to be realized.

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APPENDICES

Appendix A

Green-Yellow Sample Full-model GPA Regression Results

Variable	Unweighted		Weighted		Weighted with covariates	
Success Coaching	-0.114*	(0.057)	0.061	(0.115)	0.084	(0.096)
Aviso average model score					-62.091	(106.578)
Aviso average model score squared					36.203	(59.759)
Female					0.302	(0.096)
Asian					-0.585	(0.484)
African American					-0.419	(0.135)
Latino					-0.012	(0.125)
Native American					0.306	(0.491)
Race missing					0.244	(0.176)
Age=21-26					0.371	(0.152)
Age=>27					0.477	(0.190)
AGI missing					0.129	(0.168)
AGI>\$20736					0.077	(0.128)
Independent tax status					0.200	(0.169)
Dependency tax status missing					0.237	(0.202)
Math score missing					0.038	(0.143)
Math score>20					0.280	(0.183)
Reading placement score missing					0.296	(0.168)
Reading placement score=75.1-90					0.389	(0.178)
Reading placement score>90					0.547	(0.228)
No transfer credit					0.462	(0.206)

Appendix A (continued)

Previously received free aid	-0.297	(0.209)
Returning student with drops	-0.177	(0.173)
New student/no credit last 5 years	-0.138	(0.261)
Returning student with withdrawals	-0.334	(0.172)
New student/returning after 5 years	-0.044	(0.247)
No GPA yet	-0.152	(0.143)
GPA=2.78-3.44	0.255	(0.143)
GPA>3.44	0.558	(0.219)
If returning student, all past courses passed	0.313	(0.162)
Taking 6-9 credits	0.160	(0.196)
Taking 10-11 credits	0.591	(0.231)
Taking > 12 credits	0.355	(0.235)
No developmental math score	0.539	(0.235)
Developmental math score=6.1-7.67	0.295	(0.253)
Developmental math score>7.67	0.700	(0.254)
Student not receiving free aid	0.020	(0.262)
Student receiving free aid =>\$5729	-0.017	(0.157)
Student did not received Pell	0.037	(0.253)
%High-risk courses	-1.588	(0.974)
%High/moderate-risk courses	-1.367	(0.307)
%Moderate/low-risk courses	-0.551	(0.163)
%Online courses	-0.534	(0.140)
%000-level courses	-0.523	(0.371)
%200-level courses	-0.453	(0.244)

Appendix A (continued)

%Courses retaking					-0.219	(0.333)
Intercept	3.015***	(0.034	2.840***	(0.105)	28.253	(47.553)
<i>N</i>	1332		1332		1332	
<i>R</i> -squared	0.003		0.0008		0.1951	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Appendix B

Green-Yellow Sample University Transfer and Not University Transfer GPA Results

Variable	University Transfer		Not University Transfer	
Success Coaching	0.350*	(0.158)	0.087	(0.127)
Aviso average model score	-101.949	(187.604)	60.858	(146.989)
Aviso average model score squared	57.843	(105.217)	-32.666	(82.414)
Female	0.314*	(0.155)	0.239	(0.156)
Asian	1.166	(0.556)	-0.311	(0.965)
African American	-0.555*	(0.271)	-0.477**	(0.179)
Latino	-0.123	(0.217)	0.062	(0.173)
Native American	-2.001**	(0.571)	0.717	(0.599)
Race missing	0.045	(0.270)	0.076	(0.306)
Age=21-26	0.594*	(0.268)	0.469*	(0.213)
Age=>27	1.330***	(0.323)	0.629**	(0.233)
AGI missing	0.226	(0.265)	0.120	(0.220)
AGI>\$20736	0.366	(0.191)	0.037	(0.162)
Independent tax status	0.256	(0.285)	-0.046	(0.206)
Dependency tax status missing	-0.150	(0.389)	-0.312	(0.276)
Math score missing	-0.529*	(0.208)	0.070	(0.204)
Math score>20	-0.385	(0.278)	0.287	(0.308)
Reading placement score missing	0.783**	(0.269)	0.172	(0.178)
Reading placement score=75.1-90	0.528	(0.308)	0.374	(0.194)
Reading placement score>90	0.889*	(0.341)	0.440	(0.269)
No transfer credit	0.464	(0.280)	0.531*	(0.235)
Previously received free aid	-0.526	(0.287)	-0.371	(0.224)
Returning student with drops	0.507*	(0.214)	-0.237	(0.193)
New student/no credit last 5 years	1.435	(0.921)	-0.183	(0.261)
Returning student with withdrawals	-0.296	(0.233)	-0.540**	(0.198)
New student/returning after 5 years	0.279	(0.481)	-0.104	(0.363)
No GPA yet	-0.549	(0.279)	-0.030	(0.179)
GPA=2.78-3.44	0.296	(0.201)	0.539**	(0.163)
GPA>3.44	0.596	(0.322)	1.076***	(0.246)
If returning student, all past courses passed	0.494*	(0.218)	0.249	(0.198)
Taking 6-9 credits	0.523	(0.380)	0.107	(0.302)
Taking 10-11 credits	1.054*	(0.406)	0.839*	(0.353)
Taking > 12 credits	1.225**	(0.414)	0.590	(0.328)
No developmental math score	0.448	(0.436)	0.511*	(0.234)

Green-Yellow Sample University Transfer and Not University Transfer GPA Results
(continued)

Developmental math score=6.1-7.67	0.381	(0.430)	0.088	(0.280)
Developmental math score>7.67	0.986	(0.475)	0.698**	(0.266)
Student not receiving free aid	0.507	(0.346)	0.111	(0.327)
Student receiving free aid =>\$5729	0.177	(0.231)	-0.027	(0.198)
Student did not received Pell	-0.252	(0.367)	-0.040	(0.331)
%High-risk courses	-1.202	(1.407)	-3.149*	(1.360)
%High/moderate-risk courses	-0.981	(0.530)	-1.166**	(0.399)
%Moderate/low-risk courses	-0.970*	(0.391)	-0.335	(0.257)
%Online courses	-0.119	(0.242)	-0.472*	(0.212)
%000-level courses	-1.568	(0.921)	-0.212	(0.383)
%200-level courses	-0.635*	(0.286)	-0.239	(0.347)
%Courses retaking	-1.742***	(0.381)	0.402	(0.361)
Intercept	45.630	(83.723)	-26.743	(65.463)
<i>N</i>	271		579	
<i>R</i> -squared	0.5877		0.2962	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The subgroup “Not University Transfer” consisted of only students who were pursuing associate of applied science degrees. Diploma and certificate seeking students were not included in either subgroup.

Green-Yellow Sample Associate Degree and Not Associate Degree GPA Results

Variable	Associate Degree		Not Associate Degree	
Success Coaching	0.184	(0.118)	-0.006	(0.138)
Aviso average model score	114.498	(121.953)	0.894	(213.418)
Aviso average model score squared	-61.501	(67.953)	2.009	(121.503)
Female	0.231	(0.118)	0.084	(0.122)
Asian	0.059	(0.756)	-1.483**	(0.488)
African American	-0.409**	(0.149)	0.043	(0.227)
Latino	0.041	(0.158)	0.027	(0.169)
Native American	0.075	(0.617)	0.634***	(0.159)
Race missing	0.003	(0.205)	0.362*	(0.169)
Age=21-26	0.579**	(0.176)	-0.346	(0.217)
Age=>27	0.773***	(0.209)	0.194	(0.294)
AGI missing	0.238	(0.189)	-0.428	(0.304)
AGI>\$20736	0.166	(0.130)	-1.010***	(0.285)
Independent tax status	0.055	(0.177)	-0.492	(0.321)
Dependency tax status missing	-0.251	(0.259)	-0.875**	(0.323)
Math score missing	-0.110	(0.165)	0.347*	(0.161)
Math score>20	-0.107	(0.213)	0.579**	(0.203)
Reading placement score missing	0.241	(0.164)	0.987*	(0.438)
Reading placement score=75.1-90	0.287	(0.174)	0.757	(0.415)
Reading placement score>90	0.413*	(0.203)	-0.413	(0.794)
No transfer credit	0.363	(0.196)	1.147**	(0.396)
Previously received free aid	-0.235	(0.188)	0.502	(0.465)
Returning student with drops or withdrawals	-0.372*	(0.144)	0.300	(0.268)
New student/returning no credit 5 years	0.335	(0.256)	-0.240	(0.399)
No GPA yet	- 0.158	(0.159)	-0.620	(0.364)
GPA=2.78-3.44	0.453**	(0.134)	-0.318	(0.449)
GPA>3.44	0.632**	(0.206)	-0.412	(0.390)
If returning student, all past courses passed	0.130	(0.152)	0.116	(0.314)
Taking 6-9 credits	0.083	(0.280)	0.019	(0.229)
Taking 10-11 credits	0.668*	(0.285)	-0.313	(0.357)
Taking > 12 credits	0.556	(0.285)	-0.077	(0.274)
No developmental math score	0.382	(0.238)	-0.102	(0.369)
Developmental math score=6.1-7.67	0.280	(0.262)	-0.333	(0.357)
Developmental math score>7.67	0.704**	(0.251)	-0.359	(0.521)
Student not receiving free aid	0.188	(0.245)	0.937*	(0.475)
Student receiving free aid =>\$5729	-0.017	(0.164)	-0.073	(0.360)

Green-Yellow Sample Associate Degree and Not Associate Degree GPA Results (continued)

Student did not received Pell	-0.042	(0.242)	-0.422	(0.465)
%High/high-moderate-risk courses	-0.744*	(0.317)	-0.932	(0.969)
%Online courses	-0.358*	(0.168)	0.033	(0.196)
%000-level courses	-0.215	(0.399)	-1.439	(1.107)
%200-level courses	-0.420	(0.312)	-0.620*	(0.309)
%Courses retaking	-0.103	(0.348)	0.943	(0.730)
Intercept	-51.799	(54.688)	-0.533	(93.715)
<i>N</i>	850		482	
<i>R</i> -squared	0.2880		0.2009	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. To avoid collinearity, the covariate *%High/high-moderate-risk courses* replaced the original covariates *%High-risk courses* and *%High/moderate-risk courses*. The reference variable for *%High/high-moderate-risk courses* was *%Moderate-low/low-risk courses* which replaced *%Moderate/low-risk courses* and *%Low-risk courses*. Likewise, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Green-Yellow Sample Online Course Percentage GPA Results

Variable	Online Courses=>50%		Online Courses<50%	
Success Coaching	0.358**	(0.132)	-0.082	(0.109)
Aviso average model score	-97.919	(193.661)	-79.185	(115.775)
Aviso average model score squared	54.288	(108.756)	46.461	(64.919)
Female	0.255	(0.177)	0.262*	(0.108)
Asian	-0.569	(1.230)	-0.572	(0.447)
African American	-0.596**	(0.205)	-0.109	(0.155)
Latino	-0.038	(0.185)	0.035	(0.142)
Native American	0.485	(0.985)	0.100	(0.512)
Race missing	0.374	(0.233)	0.183	(0.221)
Age=21-26	0.267	(0.229)	0.208	(0.201)
Age=>27	0.503	(0.266)	0.402	(0.223)
AGI missing	0.306	(0.228)	-0.047	(0.178)
AGI>\$20736	0.268	(0.200)	-0.098	(0.135)
Independent tax status	0.345	(0.233)	0.286	(0.186)
Dependency tax status missing	0.574	(0.345)	0.129	(0.216)
Math score missing	-0.395	(0.186)	0.208	(0.164)
Math score>20	-0.195	(0.306)	0.445*	(0.208)
Reading placement score missing	0.564**	(0.215)	0.048	(0.184)
Reading placement score=75.1-90	0.727**	(0.261)	0.092	(0.184)
Reading placement score>90	0.876**	(0.285)	0.250	(0.279)
No transfer credit	0.415	(0.271)	0.238	(0.218)
Previously received free aid	-0.791**	(0.274)	-0.012	(0.202)
Returning student with drops	0.066	(0.242)	-0.063	(0.172)
New student/no credit last 5 years	-0.274	(0.402)	-0.207	(0.393)
Returning student with withdrawals	-0.618*	(0.261)	-0.084	(0.182)
New student/returning after 5 years	-0.988	(0.513)	0.055	(0.283)
No GPA yet	0.110	(0.208)	-0.049	(0.184)
GPA=2.78-3.44	0.137	(0.204)	0.157	(0.163)
GPA>3.44	0.361	(0.344)	0.686**	(0.234)
If returning student, all past courses passed	0.482*	(0.225)	0.063	(0.186)
Taking 6-9 credits	0.283	(0.305)	0.064	(0.208)
Taking 10-11 credits	1.223**	(0.372)	-0.052	(0.284)
Taking > 12 credits	1.012**	(0.341)	-0.019	(0.283)
No developmental math score	0.927**	(0.298)	0.342	(0.236)
Developmental math score=6.1-7.67	0.954**	(0.339)	-0.059	(0.261)
Developmental math score>7.67	1.313***	(0.352)	0.250	(0.271)

Green-Yellow Sample Online Course Percentage GPA Results (continued)

Student not receiving free aid	0.071	(0.422)	0.031	(0.346)
Student receiving free aid =>\$5729	0.169	(0.256)	-0.238	(0.178)
Student did not received Pell	-0.036	(0.436)	-0.035	(0.346)
%High-risk courses	-1.297	(1.999)	-1.721	(0.966)
%High/moderate-risk courses	-1.233*	(0.481)	-1.284***	(0.362)
%Moderate/low-risk courses	-0.545	(0.285)	-0.424*	(0.186)
%000-level courses	-1.603*	(0.630)	-0.478	(0.360)
%200-level courses	-0.088	(0.317)	-0.510*	(0.257)
%Courses retaking	-0.169	(0.491)	0.114	(0.412)
Intercept	44.513	(85.998)	36.117	(51.539)
<i>N</i>	425		907	
<i>R-squared</i>	0.4479		0.1436	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The covariate %*Online courses* was excluded from the model since it was the limiting variable for the subgroup.

Green-Yellow Sample New and Returning Students GPA Results

Variable	New		Returning	
Success Coaching	0.162	(0.128)	-0.016	(0.126)
Aviso average model score	5.990	(122.403)	-20.894	(169.734)
Aviso average model score squared	0.895	(68.119)	11.275	(96.495)
Female	0.012	(0.120)	0.324*	(0.130)
Asian	0.385	(0.247)	-0.890	(0.479)
African American	-0.325	(0.171)	-0.273	(0.199)
Latino	-0.302	(0.160)	0.311	(0.162)
Native American	-0.238	(0.776)	1.441***	(0.351)
Race missing	0.357	(0.208)	0.113	(0.258)
Age=21-26	0.156	(0.152)	0.172	(0.212)
Age=>27	0.174	(0.269)	0.418	(0.266)
AGI missing	0.321	(0.226)	0.245	(0.242)
AGI>\$20736	0.164	(0.163)	0.055	(0.203)
Independent tax status	0.090	(0.190)	0.457	(0.256)
Dependency tax status missing	0.118	(0.257)	-0.061	(0.299)
Math score missing	-0.083	(0.155)	0.125	(0.198)
Math score>20	-0.210	(0.226)	0.460*	(0.233)
Reading placement score missing	0.279	(0.219)	0.753**	(0.241)
Reading placement score=75.1-90	0.438**	(0.165)	0.470	(0.327)
Reading placement score>90	0.387*	(0.193)	0.442	(0.628)
No transfer credit	0.393	(0.207)	0.355	(0.240)
Previously received free aid	-0.038	(0.190)	-0.878	(0.817)
Taking 6-9 credits	-0.003	(0.304)	0.141	(0.196)
Taking 10-11 credits	0.492	(0.293)	0.225	(0.325)
Taking > 12 credits	0.291	(0.299)	0.206	(0.306)
No developmental math score	-0.024	(0.280)	0.967***	(0.257)
Developmental math score=6.1-7.67	0.015	(0.322)	0.554	(0.298)
Developmental math score>7.67	0.195	(0.287)	1.020**	(0.302)
Student not receiving free aid	0.015	(0.425)	-0.045	(0.413)
Student receiving free aid =>\$5729	-0.142	(0.201)	0.130	(0.220)
Student did not received Pell	-0.276	(0.418)	0.294	(0.433)
%High-risk courses	-0.580	(0.829)	-2.997	(1.616)
%High/moderate-risk courses	-0.816*	(0.353)	-0.854*	(0.409)
%Moderate/low-risk courses	-0.273	(0.204)	-0.609**	(0.229)
%Online courses	-0.620**	(0.185)	-0.241	(0.178)
%000-level courses	0.008	(0.316)	-1.694**	(0.489)
%200-level courses	-0.505	(0.326)	-0.289	(0.288)

Green-Yellow Sample New and Returning Students GPA Results (continued)

%Courses retaking	-0.100	(0.333)	-0.723	(0.586)
Intercept	-3.325	(54.964)	11.163	(74.601)
<i>N</i>	599		733	
<i>R</i> -squared	0.92326		0.1942	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Because the focus subgroup was “New Student,” the following were removed from the model used for the whole-sample analyses: *Returning student with dropped courses; New student/no credit last 5 years; Returning student with withdrawals; New student/returning after 5 years; no GPA yet; GPA=2.78-3.44; GPA>3.44; and If returning student, all past courses passed.* To avoid issues with collinearity, these covariates were also excluded from the “Returning Student” subgroup model.

Green-Yellow Sample Female and Male Students GPA Results

Variable	Female		Male	
Success Coaching	0.178	(0.109)	-0.025	(0.146)
Aviso average model score	-88.834	(138.924)	-140.560	(149.974)
Aviso average model score squared	52.363	(78.248)	79.904	(83.913)
Asian	-0.407	(1.274)	-0.744	(0.453)
African American	-0.499**	(0.150)	0.075	(0.202)
Latino	-0.039	(0.144)	0.090	(0.211)
Native American	-0.063	(0.744)	0.656	(0.635)
Race missing	0.439	(0.178)	0.088	(0.264)
Age=21-26	0.619***	(0.169)	0.092	(0.203)
Age=>27	0.685**	(0.233)	0.117	(0.247)
AGI missing	0.132	(0.187)	-0.013	(0.260)
AGI>\$20736	0.156	(0.163)	-0.089	(0.196)
Independent tax status	0.082	(0.200)	0.452	(0.243)
Dependency tax status missing	0.467	(0.240)	0.200	(0.300)
Math score missing	-0.123	(0.148)	0.134	(0.229)
Math score>20	-0.115	(0.254)	0.447	(0.252)
Reading placement score missing	0.217	(0.202)	0.343	(0.278)
Reading placement score=75.1-90	0.300	(0.192)	0.535	(0.274)
Reading placement score>90	0.490	(0.283)	0.691*	(0.310)
No transfer credit	0.288	(0.230)	0.635*	(0.319)
Previously received free aid	-0.294	(0.256)	0.033	(0.216)
Returning student with drops	-0.406*	(0.191)	0.342	(0.212)
New student/no credit last 5 years	0.073	(0.411)	0.305	(0.432)
Returning student with withdrawals	-0.333	(0.221)	-0.154	(0.209)
New student/returning after 5 years	0.036	(0.276)	-0.286	(0.356)
No GPA yet	-0.002	(0.172)	-0.386	(0.262)
GPA=2.78-3.44	0.184	(0.165)	0.300	(0.229)
GPA>3.44	0.827**	(0.259)	0.410	(0.349)
If returning student, all past courses passed	0.162	(0.210)	0.386	(0.224)
Taking 6-9 credits	0.172	(0.211)	0.343	(0.276)
Taking 10-11 credits	0.744**	(0.234)	0.380	(0.374)
Taking > 12 credits	0.489*	(0.240)	0.187	(0.336)
No developmental math score	0.180	(0.265)	0.609	(0.319)
Developmental math score=6.1-7.67	0.056	(0.274)	0.119	(0.379)
Developmental math score>7.67	0.424	(0.291)	0.687	(0.354)
Student not receiving free aid	-0.178	(0.400)	-0.158	(0.441)
Student receiving free aid =>\$5729	0.114	(0.179)	-0.411	(0.249)

Green-Yellow Sample Female and Male Students GPA Results (continued)

Student did not received Pell	0.241	(0.371)	-0.103	(0.481)
%High-risk courses	-2.085	(1.472)	-1.691	(1.404)
%High/moderate-risk courses	-1.015**	(0.330)	-1.617*	(0.670)
%Moderate/low-risk courses	-0.244	(0.217)	-0.570*	(0.236)
%Online courses	-0.711***	(0.163)	0.050	(0.187)
%000-level courses	-1.469***	(0.396)	0.282	(0.382)
%200-level courses	-0.379	(0.299)	-0.384	(0.300)
%Courses retaking	0.397	(0.307)	-1.330	(0.684)
Intercept	39.879	(61.697)	63.212	(66.881)
<i>N</i>	826		506	
<i>R</i> -squared	0.2893		0.2486	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Since the model limited observation based on *Female*, the variable was not included in the model.

Appendix C

Green-Yellow Sample Full-model Logit Results for Fall-to-Spring Retention

Variable	Unweighted		Weighted		Weighted with covariates	
Success Coaching	0.067	(0.130)	0.207	(0.205)	0.358	(0.221)
Aviso average model score					-339.019	(309.162)
Aviso average model score squared					195.565	(175.618)
Female					0.297	(0.228)
Asian					0.097	(0.986)
African American					0.270	(0.332)
Latino					0.069	(0.283)
Native American					0.945	(1.021)
Race missing					0.917	(0.530)
Age=21-26					-0.654	(0.381)
Age=>27					-0.213	(0.539)
AGI missing					-0.264	(0.524)
AGI>\$20736					0.218	(0.317)
Independent tax status					-0.310	(0.417)
Dependency tax status missing					0.051	(0.632)
Math score missing					-0.597	(0.394)
Math score>20					0.481	(0.522)
Reading placement score missing					0.087	(0.434)
Reading placement score=75.1-90					-0.142	(0.470)
Reading placement score>90					-0.574	(0.574)
No transfer credit					0.190	(0.457)
Previously received free aid					0.637	(0.467)

Appendix C (continued)

Returning student with drops	-0.004	(0.370)
New student/no credit last 5 years	-1.557	(0.865)
Returning student with withdrawals	-0.253	(0.398)
New student/returning after 5 years	0.387	(1.254)
No GPA yet	-0.609	(0.432)
GPA=2.78-3.44	0.510	(0.402)
GPA>3.44	0.106	(0.662)
If returning student, all past courses passed	0.034	(0.446)
Taking 6-9 credits	0.884	(0.360)
Taking 10-11 credits	1.793	(0.572)
Taking > 12 credits	1.780	(0.527)
No developmental math score	0.311	(0.445)
Developmental math score=6.1-7.67	0.859	(0.485)
Developmental math score>7.67	0.652	(0.629)
Student not receiving free aid	0.782	(0.630)
Student receiving free aid =>\$5729	0.723	(0.451)
Student did not received Pell	-0.481	(0.644)
%High-risk courses	-2.600	(3.307)
%High/moderate-risk courses	-2.676	(0.754)
%Moderate/low-risk courses	-1.033	(0.460)
%Online courses	-0.115	(0.313)
%000-level courses	0.566	(0.686)
%200-level courses	0.522	(0.412)
%Courses retaking	-0.339	(0.612)

Appendix C (continued)

Intercept	0.985***	(0.077)	0.845***	(0.177)	146.775	(136.028)
<i>N</i>	1332		1332		1332	
Pseudo <i>R</i> ²	0.0002		0.0018		0.1843	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Appendix D

Green-Yellow Sample University Transfer and Not University Transfer Logit Results

Variable	University Transfer		Not University Transfer	
Success Coaching	-0.262	(0.596)	0.064	(0.347)
Aviso average model score	-246.782	(605.220)	-617.764	(550.885)
Aviso average model score squared	136.941	(341.036)	349.644	(313.063)
Female	0.754	(0.572)	0.651	(0.408)
Race category 1	-0.511	(1.162)	0.121	(0.495)
Race category 2	0.030	(0.738)	1.158*	(0.535)
Age=21-26	0.464	(0.814)	-0.456	(0.538)
Age=>27	1.933	(1.254)	0.916	(0.676)
AGI missing	-3.552**	(1.313)	1.535*	(0.685)
AGI>\$20736	-0.246	(0.643)	0.438	(0.428)
Independent tax status	-1.245	(0.947)	-0.193	(0.552)
Dependency tax status missing	2.834	(1.465)	-1.333	(0.837)
Math score missing	-0.701	(0.831)	-0.786	(0.616)
Math score>20	0.378	(1.150)	0.287	(1.044)
Reading placement score missing	-0.167	(1.936)	0.186	(0.578)
Reading placement score=75.1-90	2.941	(2.187)	-0.765	(0.609)
Reading placement score>90	-0.811	(1.446)	-1.029	(0.728)
No transfer credit	-0.272	(1.545)	0.662	(0.550)
Previously received free aid	1.599	(1.257)	-0.352	(0.544)
Returning student with drops or withdrawals	-0.489	(1.550)	-0.560	(0.500)
New student/returning no credit 5 years	-1.003	(2.116)	-0.663	(1.554)
No GPA yet	-1.651	(1.026)	0.053	(0.569)
GPA=2.78-3.44	0.080	(1.073)	1.638**	(0.562)
GPA>3.44	-0.465	(1.672)	1.119	(0.747)
If returning student, all past courses passed	0.098	(1.106)	0.263	(0.569)
Taking 6-9 credits	3.258**	(1.002)	0.827	(0.599)
Taking 10-11 credits	3.256**	(1.194)	2.460**	(0.821)
Taking > 12 credits	4.395**	(1.306)	2.422**	(0.781)
No developmental math score	0.416	(0.872)	0.937	(0.573)
Developmental math score=6.1-7.67	0.512	(1.057)	1.383*	(0.641)
Developmental math score>7.67	0.979	(1.154)	1.463	(0.838)
Student not receiving free aid	1.811	(1.075)	0.192	(0.754)
Student receiving free aid =>\$5729	2.193*	(0.966)	-0.264	(0.590)
Student did not received Pell	-1.868	(1.064)	-0.078	(0.885)

Green-Yellow Sample University Transfer and Not University Transfer Logit Results
(continued)

%High-risk courses	-4.321	(5.356)	-5.403	(3.958)
%High/moderate-risk courses	-4.550	(2.548)	-4.732***	(1.102)
%Moderate/low-risk courses	-0.764	(1.198)	-1.035	(0.589)
%Online courses	-1.573	(0.864)	-0.255	(0.488)
%000-level courses	-0.653	(1.751)	0.783	(0.757)
%200-level courses	1.082	(1.821)	0.829	(0.803)
%Courses retaking	-1.243	(2.141)	-0.576	(0.752)
Intercept	110.651	(267.351)	271.557	(242.157)
<i>N</i>	271		579	
Pseudo <i>R</i> ²	0.4183		0.2924	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White*, *Asian*, *Native American*, and *Race missing*. The “Race category” variable was originally an ordinal variable provided in *Aviso*’s dataset. To avoid other collinearity issues, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Green-Yellow Sample Associate Degree and Not Associate Degree Logit Results

Variable	Associate Degree		Not Associate Degree	
Success Coaching	-0.169	(0.275)	1.023*	(0.454)
Aviso average model score	-570.252	(350.534)	-588.126	(719.186)
Aviso average model score squared	325.073	(198.732)	369.283	(414.426)
Female	0.645*	(0.310)	-0.428	(0.381)
Asian	-0.163	(1.447)	-0.164	(1.842)
African American	0.514	(0.396)	0.966	(0.594)
Latino	0.916*	(0.425)	0.519	(0.439)
Native American	1.386	(1.276)	-0.396	(1.048)
Race missing	0.743	(0.767)	1.105	(0.940)
Age=21-26	-0.405	(0.456)	-2.133*	(0.968)
Age=>27	0.804	(0.547)	-0.792	(1.146)
AGI missing	0.189	(0.565)	-1.736	(1.455)
AGI>\$20736	0.337	(0.323)	-0.980	(1.238)
Independent tax status	-0.720	(0.419)	-1.596	(1.352)
Dependency tax status missing	-0.383	(0.704)	-0.380	(1.979)
Math score missing	-0.543	(0.464)	0.226	(0.648)
Math score>20	0.543	(0.726)	0.564	(0.851)
Reading placement score missing	-0.005	(0.486)	-0.947	(1.723)
Reading placement score=75.1-90	-0.359	(0.513)	-3.239	(2.748)
Reading placement score>90	-0.699	(0.623)	-5.788	(3.339)
No transfer credit	0.063	(0.491)	0.138	(1.926)
Previously received free aid	0.322	(0.456)	7.757**	(2.839)
Returning student with drops or withdrawals	-0.474	(0.390)	2.968*	(1.486)
New student/returning no credit 5 years	-0.713	(0.931)	-1.188	(1.360)
No GPA yet	-0.108	(0.488)	-3.732	(2.410)
GPA=2.78-3.44	0.931*	(0.406)	-3.878	(2.738)
GPA>3.44	0.788	(0.676)	-9.741**	(3.079)
If returning student, all past courses passed	-0.322	(0.433)	0.079	(2.678)
Taking 6-9 credits	1.034*	(0.451)	-0.045	(0.528)
Taking 10-11 credits	1.997**	(0.577)	-2.737*	(1.272)
Taking > 12 credits	2.324***	(0.544)	0.843	(0.991)
No developmental math score	0.674	(0.467)	-0.292	(1.638)
Developmental math score=6.1-7.67	1.207*	(0.528)	0.717	(1.856)
Developmental math score>7.67	1.356	(0.745)	-0.841	(1.838)
Student not receiving free aid	1.049	(0.646)	-1.192	(2.267)
Student receiving free aid =>\$5729	0.162	(0.421)	-0.339	(1.827)

Green-Yellow Sample Associate Degree and Not Associate Degree Logit Results (continued)

Student did not received Pell	-1.040	(0.691)	3.776*	(1.880)
%High/high-moderate-risk courses	-2.795***	(0.722)	-1.946	(2.096)
%Online courses	-0.403	(0.394)	0.780	(0.547)
%000-level courses	-0.606	(0.690)	-55.704***	(9.764)
%200-level courses	-0.067	(0.904)	-55.547***	(9.803)
%Courses retaking	-0.624	(0.603)	7.379*	(3.549)
Intercept	249.863	(154.521)	284.533	(315.923)
<i>N</i>	850		482	
Pseudo <i>R</i> ²	0.2496		0.2382	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. To avoid collinearity, the covariate *%High/high-moderate-risk courses* replaced the original covariates *%High-risk courses* and *%High/moderate-risk courses*. The reference variable for *%High/high-moderate-risk courses* was *%Moderate-low/low-risk courses* which replaced *%Moderate/low-risk courses* and *%Low-risk courses*. Likewise, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Green-Yellow Sample Online Course Percentage Logit Results

Variable	Online Courses>=>50%		Online Courses<50%	
Success Coaching	-0.065	(0.386)	0.589*	(0.295)
Aviso average model score	-806.391	(565.909)	-447.125	(439.581)
Aviso average model score squared	455.716	(322.263)	265.124	(249.535)
Female	-0.103	(0.448)	0.305	(0.272)
Race category 1	0.703	(0.539)	-0.045	(0.431)
Race category 2	0.555	(0.622)	-0.131	(0.354)
Age=21-26	-0.553	(0.539)	-1.271*	(0.496)
Age=>27	0.122	(0.621)	-0.616	(0.692)
AGI missing	-0.534	(0.890)	-0.201	(0.566)
AGI>\$20736	0.520	(0.528)	0.065	(0.386)
Independent tax status	-1.085	(0.682)	0.059	(0.548)
Dependency tax status missing	-0.250	(1.283)	-0.033	(0.726)
Math score missing	-0.551	(0.757)	-0.284	(0.448)
Math score>20	0.792	(0.896)	0.354	(0.642)
Reading placement score missing	0.362	(0.644)	-0.194	(0.681)
Reading placement score=75.1-90	-0.002	(0.781)	-0.261	(0.653)
Reading placement score>90	-0.811	(0.808)	-0.197	(0.800)
No transfer credit	0.160	(0.664)	-0.622	(0.657)
Previously received free aid	0.536	(0.587)	0.710	(0.705)
Returning student with drops or withdrawals	-0.420	(0.564)	0.329	(0.549)
New student/returning no credit 5 years	1.008	(1.624)	-1.350	(0.779)
No GPA yet	0.237	(0.682)	-1.355*	(0.640)
GPA=2.78-3.44	0.423	(0.551)	0.631	(0.599)
GPA>3.44	-0.028	(0.914)	-0.064	(0.842)
If returning student, all past courses passed	-0.082	(0.594)	0.771	(0.611)
Taking 6-9 credits	0.777	(0.569)	0.935*	(0.453)
Taking 10-11 credits	1.200	(0.900)	2.029**	(0.768)
Taking > 12 credits	1.783*	(0.754)	2.004**	(0.678)
No developmental math score	0.455	(0.649)	0.689	(0.564)
Developmental math score=6.1-7.67	0.963	(0.768)	1.327*	(0.633)
Developmental math score>7.67	2.252*	(1.052)	0.057	(0.706)
Student not receiving free aid	0.668	(1.053)	1.236	(0.757)
Student receiving free aid =>\$5729	-0.094	(0.631)	0.641	(0.523)
Student did not received Pell	-1.861	(1.146)	-0.296	(0.731)
%High-risk courses	-3.868	(5.996)	-5.315	(4.753)
%High/moderate-risk courses	-1.434	(1.080)	-3.976***	(1.087)

Green-Yellow Sample Online Course Percentage Logit Results (continued)

%Moderate/low-risk courses	-0.621	(0.640)	-1.185*	(0.571)
%000-level courses	-0.198	(1.539)	0.664	(0.777)
%200-level courses	0.968	(0.717)	0.343	(0.476)
%Courses retaking	-0.038	(0.902)	-0.748	(0.832)
Intercept	357.378	(248.226)	188.251	(193.644)
<i>N</i>	425		907	
Pseudo <i>R</i> ²	0.2281		0.2439	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The covariate %*Online courses* was excluded from the model since it was the limiting variable for the subgroup analysis. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White*, *Asian*, *Native American*, and *Race missing*. The “Race category” variable was originally an ordinal variable provided in Aviso’s dataset. To avoid other collinearity issues, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Green-Yellow Sample New and Returning Students Logit Results

Variable	New		Returning	
Success Coaching	-0.048	(0.338)	0.378	(0.293)
Aviso average model score	-509.635	(380.497)	-482.217	(463.856)
Aviso average model score squared	295.239	(213.973)	278.608	(264.097)
Female	0.171	(0.407)	0.126	(0.280)
Asian	-0.709	(1.695)	0.075	(1.339)
African American	0.535	(0.474)	0.547	(0.451)
Latino	0.362	(0.458)	-0.095	(0.390)
Native American	1.246	(1.791)	0.896	(1.255)
Race missing	2.290*	(1.020)	0.294	(0.628)
Age=21-26	-0.615	(0.505)	-1.152*	(0.531)
Age=>27	0.170	(0.660)	-0.663	(0.741)
AGI missing	0.185	(0.619)	-0.112	(0.819)
AGI>\$20736	0.281	(0.431)	0.147	(0.463)
Independent tax status	-0.445	(0.525)	0.017	(0.624)
Dependency tax status missing	0.054	(0.811)	-0.323	(0.951)
Math score missing	-0.529	(0.597)	-0.242	(0.460)
Math score>20	0.769	(0.848)	0.096	(0.570)
Reading placement score missing	-0.310	(0.526)	1.751*	(0.715)
Reading placement score=75.1-90	-0.520	(0.575)	1.586	(1.017)
Reading placement score>90	-1.234*	(0.586)	2.893*	(1.153)
No transfer credit	-0.083	(0.492)	1.786	(1.705)
Previously received free aid	0.732	(0.454)	-0.806	(1.660)
Taking 6-9 credits	0.922	(0.565)	1.068*	(0.460)
Taking 10-11 credits	2.019*	(0.834)	0.978	(0.791)
Taking > 12 credits	1.629*	(0.751)	1.970**	(0.651)
No developmental math score	0.108	(0.535)	0.190	(0.565)
Developmental math score=6.1-7.67	0.001	(0.608)	1.754*	(0.850)
Developmental math score>7.67	1.579	(1.124)	-0.074	(0.721)
Student not receiving free aid	0.518	(0.971)	1.398	(0.891)
Student receiving free aid =>\$5729	-0.359	(0.636)	1.398*	(0.635)
Student did not received Pell	-0.937	(1.084)	-0.629	(0.774)
%High/high-moderate-risk courses	-2.491***	(0.708)	-1.568	(1.338)
%Online courses	-1.342**	(0.461)	1.052*	(0.425)
%000-level courses	0.280	(0.975)	0.102	(0.820)
%200-level courses	1.507	(0.808)	-0.146	(0.498)
%Courses retaking	-0.459	(0.587)	1.943	(2.053)
Intercept	221.027	(169.046)	204.776	(203.544)

Green-Yellow Sample New and Returning Students Logit Results (continued)

<i>N</i>	599	733
Pseudo <i>R</i> ²	0.316	0.164

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Because the focus subgroup was “New Student,” the following were removed from the model used for the whole-sample analyses: *Returning student with dropped courses; New student/no credit last 5 years; Returning student with withdrawals; New student/returning after 5 years; no GPA yet; GPA=2.78-3.44; GPA>3.44; and If returning student, all past courses passed.* To avoid issues with collinearity, these covariates were also excluded from the “Returning Student” subgroup model. Likewise, the covariate *%High/high-moderate-risk courses* replaced the original covariates *%High-risk courses* and *%High/moderate-risk courses*. The reference variable for *%High/high-moderate-risk courses* was *%Moderate-low/low-risk courses* which replaced *%Moderate/low-risk courses* and *%Low-risk courses*.

Green-Yellow Sample Female and Male Students Logit Results

Variable	Female		Male	
Success Coaching	-0.093	(0.259)	0.906	(0.468)
Aviso average model score	-511.128	(306.854)	-224.294	(568.434)
Aviso average model score squared	289.656	(173.576)	148.282	(321.601)
Asian	-1.000	(2.564)	0.150	(1.543)
African American	0.464	(0.396)	1.602*	(0.769)
Latino	-0.149	(0.346)	1.150*	(0.580)
Native American	2.139	(1.425)	-1.007	(1.598)
Race missing	0.867	(0.618)	0.940	(0.758)
Age=21-26	0.583	(0.408)	-1.813**	(0.614)
Age=>27	1.424**	(0.517)	-1.757*	(0.827)
AGI missing	0.638	(0.651)	-1.354	(1.001)
AGI>\$20736	0.345	(0.397)	-0.109	(0.665)
Independent tax status	-1.416**	(0.473)	0.139	(0.669)
Dependency tax status missing	-0.822	(0.811)	1.187	(1.234)
Math score missing	-0.765	(0.464)	0.398	(0.542)
Math score>20	0.406	(0.684)	1.188	(0.786)
Reading placement score missing	-0.252	(0.571)	0.826	(0.960)
Reading placement score=75.1-90	-0.393	(0.641)	-0.292	(1.105)
Reading placement score>90	-1.273	(0.695)	0.012	(0.989)
No transfer credit	-0.185	(0.608)	0.557	(0.691)
Previously received free aid	0.550	(0.519)	0.639	(0.862)
Returning student with drops or withdrawals	-0.183	(0.463)	-0.020	(0.656)
New student/returning no credit 5 years	-0.884	(0.851)	-0.330	(1.138)
No GPA yet	0.224	(0.581)	-2.774**	(1.019)
GPA=2.78-3.44	0.944*	(0.478)	-1.215	(0.880)
GPA>3.44	0.624	(0.934)	-1.772	(1.115)
If returning student, all past courses passed	-0.275	(0.472)	-0.281	(0.868)
Taking 6-9 credits	1.102**	(0.406)	0.506	(0.659)
Taking 10-11 credits	2.253***	(0.624)	0.381	(0.873)
Taking > 12 credits	2.567***	(0.591)	1.174	(0.774)
No developmental math score	-0.243	(0.523)	0.439	(0.675)
Developmental math score=6.1-7.67	0.287	(0.596)	2.089*	(1.036)
Developmental math score>7.67	0.847	(0.902)	-0.293	(0.833)
Student not receiving free aid	0.344	(0.861)	1.449	(1.414)
Student receiving free aid =>\$5729	-0.274	(0.520)	0.256	(0.655)
Student did not received Pell	-1.027	(0.874)	-0.753	(1.235)
%High/high-moderate-risk courses	-2.122**	(0.734)	-1.825	(1.466)

Green-Yellow Sample Female and Male Students Logit Results (continued)

%Online courses	-0.593	(0.369)	0.226	(0.551)
%000-level courses	0.330	(0.745)	0.041	(1.406)
%200-level courses	1.310*	(0.575)	-0.076	(0.647)
%Courses retaking	-0.336	(0.683)	0.851	(1.225)
Intercept	226.379	(135.469)	82.479	(251.114)
<i>N</i>	826		506	
Pseudo <i>R</i> ²	0.2506		0.2532	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Since the model limited observation based on *Female*, the variable was not included in the model. To avoid collinearity, the covariate *%High/high-moderate-risk courses* replaced the original covariates *%High-risk courses* and *%High/moderate-risk courses*. The reference variable for *%High/high-moderate-risk courses* was *%Moderate-low/low-risk courses* which replaced *%Moderate/low-risk courses* and *%Low-risk courses*. Likewise, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Appendix E

Yellow-Red Sample Full-model Regression Results for Semester GPA

Variable	Unweighted		Weighted		Weighted with covariates	
Success Coaching	0.277**	(0.084)	0.063	(0.145)	0.008	(0.108)
Aviso average model score					-19.500	(30.439)
Aviso average model score squared					9.941	(18.987)
Female					0.217	(0.130)
Asian					0.666	(0.373)
African American					-0.411	(0.161)
Latino					-0.162	(0.138)
Native American					-1.879***	(0.393)
Race missing					0.022	(0.199)
Age=21-26					0.121	(0.149)
Age=>27					0.419	(0.214)
AGI missing					-0.769***	(0.202)
AGI>\$20736					-0.211	(0.147)
Independent tax status					0.021	(0.158)
Dependency tax status missing					0.404	(0.246)
Math score missing					-0.301	(0.177)
Math score>20					-0.085	(0.288)
Reading placement score missing					0.130	(0.168)
Reading placement score=75.1-90					0.618***	(0.158)
Reading placement score>90					0.546*	(0.221)
No transfer credit					-0.017	(0.180)
Previously received free aid					-0.737***	(0.197)

Appendix E (continued)

Returning student with drops	0.086	(0.122)
New student/no credit last 5 years	-0.722	(0.582)
Returning student with withdrawals	-0.512**	(0.169)
New student/returning after 5 years	0.012	(0.352)
No GPA yet	0.127	(0.195)
GPA=2.78-3.44	0.312	(0.164)
GPA>3.44	1.272***	(0.320)
If returning student, all past courses passed	0.590***	(0.155)
Taking 6-9 credits	0.219	(0.205)
Taking 10-11 credits	0.103	(0.280)
Taking > 12 credits	0.575*	(0.258)
No developmental math score	0.648***	(0.170)
Developmental math score=6.1-7.67	0.300	(0.195)
Developmental math score>7.67	0.553*	(0.245)
Student not receiving free aid	0.345	(0.449)
Student receiving free aid =>\$5729	0.496*	(0.248)
Student did not received Pell	0.521	(0.479)
%High-risk courses	-3.012***	(0.550)
%High/moderate-risk courses	-1.173***	(0.335)
%Moderate/low-risk courses	-0.522*	(0.229)
%Online courses	-0.460**	(0.175)
%000-level courses	0.274	(0.307)
%200-level courses	0.027	(0.262)
%Courses retaking	-0.127	(0.240)

Appendix E (continued)

Intercept	2.342***	0.062	2.557***	0.134	11.651	(12.149)
<i>N</i>	699		699		699	
R-squared	0.0153		0.0008		0.2489	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Appendix F

Yellow-Red Sample University Transfer and Not University Transfer GPA Results

Variable	University Transfer		Not University Transfer	
Success Coaching	0.336	(0.202)	0.025	(0.123)
Aviso average model score	-59.466	(57.614)	20.274	(43.264)
Aviso average model score squared	35.095	(35.848)	-16.051	(27.193)
Female	-0.040	(0.195)	0.402*	(0.186)
Asian	1.679***	(0.454)	0.167	(0.582)
African American	-0.943***	(0.241)	-0.360	(0.204)
Latino	-0.109	(0.239)	-0.167	(0.178)
Native American	-1.874**	(0.643)	0.773	(0.541)
Race missing	0.622*	(0.293)	-0.295	(0.325)
Age=21-26	-0.157	(0.299)	0.015	(0.188)
Age=>27	0.155	(0.446)	0.130	(0.272)
AGI missing	0.044	(0.365)	-0.778***	(0.213)
AGI>\$20736	-0.414	(0.240)	-0.161	(0.168)
Independent tax status	0.144	(0.368)	0.063	(0.195)
Dependency tax status missing	-0.456	(0.418)	0.086	(0.315)
Math score missing	-0.106	(0.239)	-0.279	(0.196)
Math score>20	-0.051	(0.300)	-0.633	(0.440)
Reading placement score missing	0.178	(0.302)	0.061	(0.184)
Reading placement score=75.1-90	0.226	(0.265)	0.580**	(0.185)
Reading placement score>90	0.280	(0.359)	0.333	(0.244)
No transfer credit	-0.370	(0.334)	-0.163	(0.238)
Previously received free aid	0.575	(0.372)	-1.005***	(0.243)
Returning student with drops	-0.042	(0.208)	0.184	(0.163)
New student/no credit last 5 years	-2.464*	(0.979)	-0.064	(0.725)
Returning student with withdrawals	-0.211	(0.212)	-0.448*	(0.210)
New student/returning after 5 years	-0.390	(0.677)	-0.913	(0.839)
No GPA yet	-0.392	(0.351)	0.415	(0.230)
GPA=2.78-3.44	-0.017	(0.307)	0.344	(0.189)
GPA>3.44	1.006	(0.569)	1.696***	(0.356)
If returning student, all past courses passed	0.255	(0.357)	0.445*	(0.185)
Taking 6-9 credits	1.067	(0.550)	0.591*	(0.247)
Taking 10-11 credits	0.451	(0.596)	0.707*	(0.341)
Taking > 12 credits	1.014	(0.638)	0.940**	(0.293)
No developmental math score	0.738*	(0.322)	0.588*	(0.233)

Yellow-Red Sample University Transfer and Not University Transfer GPA Results
(continued)

Developmental math score=6.1-7.67	0.597	(0.316)	0.180	(0.211)
Developmental math score>7.67	0.280	(0.432)	0.807**	(0.255)
Student not receiving free aid	1.670*	(0.680)	0.111	(0.313)
Student receiving free aid =>\$5729	0.958**	(0.301)	0.233	(0.262)
Student did not received Pell	-1.062	(0.750)	0.685*	(0.298)
%High-risk courses	-2.287*	(1.105)	-2.964***	(0.644)
%High/moderate-risk courses	-2.393**	(0.677)	-1.189**	(0.426)
%Moderate/low-risk courses	-0.465	(0.432)	-0.673*	(0.270)
%Online courses	0.404	(0.277)	-0.951***	(0.243)
%000-level courses	1.737*	(0.827)	0.401	(0.363)
%200-level courses	0.303	(0.480)	0.392	(0.336)
%Courses retaking	-1.252*	(0.553)	0.108	(0.284)
Intercept	25.997	(22.805)	-3.234	(17.187)
<i>N</i>	186		414	
<i>R</i> -squared	0.601		0.3412	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Yellow-Red Sample Associate Degree Logit Results

Variable	Associate Degree	
Success Coaching	0.175	(0.291)
Aviso average model score	75.211	(80.944)
Aviso average model score squared	-50.886	(51.114)
Female	-0.046	(0.355)
Race category 1	-0.382	(0.474)
Race category 2	-0.272	(0.441)
Age=21-26	0.017	(0.440)
Age=>27	0.674	(0.678)
AGI missing	-0.912	(0.612)
AGI>\$20736	-0.078	(0.389)
Independent tax status	-0.490	(0.560)
Dependency tax status missing	0.400	(0.768)
Math score missing	0.190	(0.450)
Math score>20	0.267	(0.786)
Reading placement score missing	0.087	(0.471)
Reading placement score=75.1-90	1.080*	(0.508)
Reading placement score>90	0.154	(0.587)
No transfer credit	0.918	(0.550)
Previously received free aid	-0.415	(0.581)
Returning student with drops	0.802*	(0.406)
New student/no credit last 5 years	0.280	(1.907)
Returning student with withdrawals	-0.985*	(0.488)
New student/returning after 5 years	-0.279	(1.449)
No GPA yet	0.622	(0.561)
GPA=2.78-3.44	2.119***	(0.598)
GPA>3.44	8.471***	(1.463)
If returning student, all past courses passed	-0.139	(0.463)
Taking 6-9 credits	-0.169	(0.571)
Taking 10-11 credits	1.868*	(0.864)
Taking > 12 credits	1.655*	(0.744)
No developmental math score	1.102*	(0.490)
Developmental math score=6.1-7.67	0.680	(0.499)
Developmental math score>7.67	1.491*	(0.600)
Student not receiving free aid	1.617	(0.869)
Student receiving free aid =>\$5729	1.626**	(0.564)
Student did not received Pell	0.285	(0.896)
%High-risk courses	-2.734	(1.635)

Yellow-Red Sample Associate Degree Logit Results (continued)

%High/moderate-risk courses	-1.922*	(0.909)
%Moderate/low-risk courses	-0.909	(0.666)
%Online courses	-0.559	(0.435)
%000-level courses	1.325	(0.942)
%200-level courses	0.850	(0.703)
%Courses retaking	-0.947	(0.817)
Intercept	-29.293	(31.898)
N	600	
Pseudo R2	0.2179	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The size of the non-associate degree subgroup was too small ($N=99$) to analyze with the logit model. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White, Asian, Native American*, and *Race missing*. The “Race category” variable was originally an ordinal variable provided in Aviso’s dataset.

Yellow-Red Sample Online Course Percentage GPA Results

Variable	Online Courses=>50%		Online Courses<50%	
Success Coaching	0.210	(0.179)	0.005	(0.137)
Aviso average model score	-30.343	(47.247)	-35.949	(39.105)
Aviso average model score squared	12.848	(29.660)	23.092	(23.992)
Female	-0.055	(0.207)	0.083	(0.159)
Asian	0.358	(0.414)	0.937**	(0.348)
African American	-0.820**	(0.245)	-0.253	(0.190)
Latino	-0.161	(0.208)	-0.029	(0.166)
Native American	-0.072	(0.586)	-1.427**	(0.420)
Race missing	-0.588	(0.324)	0.354	(0.252)
Age=21-26	0.526	(0.266)	0.010	(0.182)
Age=>27	0.361	(0.370)	0.547*	(0.238)
AGI missing	-0.961**	(0.310)	-0.533**	(0.182)
AGI>\$20736	-0.175	(0.237)	-0.107	(0.181)
Independent tax status	0.073	(0.282)	-0.035	(0.199)
Dependency tax status missing	0.534	(0.365)	0.034	(0.242)
Math score missing	-0.189	(0.249)	-0.170	(0.200)
Math score>20	0.089	(0.497)	-0.133	(0.301)
Reading placement score missing	0.157	(0.326)	0.204	(0.201)
Reading placement score=75.1-90	0.336	(0.273)	0.526*	(0.204)
Reading placement score>90	0.514	(0.368)	0.317	(0.307)
No transfer credit	-0.029	(0.282)	-0.154	(0.212)
Previously received free aid	-0.523	(0.294)	-0.447	(0.244)
Returning student with drops	0.237	(0.193)	-0.075	(0.160)
New student/no credit last 5 years	-0.127	(1.360)	-1.451**	(0.542)
Returning student with withdrawals	-0.538*	(0.210)	-0.163	(0.215)
New student/returning after 5 years	-0.767	(0.720)	0.353	(0.355)
No GPA yet	0.052	(0.354)	0.142	(0.248)
GPA=2.78-3.44	0.048	(0.317)	0.258	(0.195)
GPA>3.44	1.554**	(0.460)	0.590	(0.380)
If returning student, all past courses passed	0.472	(0.294)	0.564**	(0.186)
Taking 6-9 credits	0.032	(0.321)	0.592*	(0.269)
Taking 10-11 credits	0.940*	(0.405)	-0.064	(0.351)
Taking > 12 credits	0.816*	(0.381)	0.580	(0.347)
No developmental math score	0.839**	(0.306)	0.548**	(0.200)
Developmental math score=6.1-7.67	0.865*	(0.331)	0.191	(0.237)
Developmental math score>7.67	0.621	(0.398)	0.330	(0.302)

Yellow-Red Sample Online Course Percentage GPA Results (continued)

Student not receiving free aid	0.301	(0.548)	0.249	(0.470)
Student receiving free aid =>\$5729	0.696	(0.355)	0.484	(0.301)
Student did not received Pell	0.770	(0.570)	0.500	(0.538)
%High-risk courses	-3.397***	(0.888)	-2.288**	(0.695)
%High/moderate-risk courses	-0.775	(0.483)	-0.822	(0.477)
%Moderate/low-risk courses	-0.729*	(0.331)	-0.116	(0.328)
%000-level courses	0.569	(0.544)	0.485	(0.326)
%200-level courses	0.288	(0.373)	-0.093	(0.358)
%Courses retaking	0.115	(0.304)	-0.424	(0.325)
Intercept	17.504	(18.715)	15.782	(15.765)
<i>N</i>	285		414	
<i>R</i> -squared	0.4556		0.2442	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The covariate %*Online courses* was excluded from the model since it was the limiting variable for the subgroup.

Yellow-Red Sample New and Returning Students GPA Results

Variable	New		Returning	
Success Coaching	-0.096	(0.120)	0.176	(0.226)
Aviso average model score	26.917	(35.822)	-74.445	(69.631)
Aviso average model score squared	-15.361	(22.112)	45.616	(44.474)
Female	0.224	(0.153)	-0.034	(0.251)
Asian	0.745**	(0.285)	0.337	(0.421)
African American	-0.464**	(0.167)	-0.324	(0.268)
Latino	-0.061	(0.148)	-0.040	(0.274)
Native American	-1.798***	(0.417)	-0.502	(1.154)
Race missing	0.070	(0.223)	-0.585	(0.401)
Age=21-26	0.132	(0.158)	-0.127	(0.445)
Age=>27	0.628**	(0.204)	-0.483	(0.530)
AGI missing	-0.433*	(0.171)	-0.949	(0.332)
AGI>\$20736	-0.208	(0.150)	-0.666*	(0.283)
Independent tax status	-0.095	(0.182)	0.130	(0.420)
Dependency tax status missing	-0.106	(0.223)	0.777	(0.467)
Math score missing	-0.053	(0.216)	-0.597*	(0.269)
Math score>20	-0.038	(0.315)	0.002	(0.616)
Reading placement score missing	0.167	(0.184)	0.053	(0.388)
Reading placement score=75.1-90	0.408**	(0.155)	0.277	(0.553)
Reading placement score>90	-0.007	(0.221)	1.776*	(0.707)
No transfer credit	0.071	(0.183)	0.521	(0.479)
Previously received free aid	-0.178	(0.187)	-0.862	(0.906)
Taking 6-9 credits	0.252	(0.296)	-0.054	(0.378)
Taking 10-11 credits	0.318	(0.357)	-0.297	(0.456)
Taking > 12 credits	0.397	(0.339)	0.425	(0.401)
No developmental math score	0.260	(0.201)	0.583	(0.317)
Developmental math score=6.1-7.67	0.465*	(0.207)	0.218	(0.287)
Developmental math score>7.67	0.108	(0.230)	0.742	(0.509)
Student not receiving free aid	0.912*	(0.440)	-0.833	(0.641)
Student receiving free aid =>\$5729	-0.073	(0.201)	0.454	(0.364)
Student did not received Pell	-0.745	(0.457)	1.482**	(0.535)
%High-risk courses	-0.529	(0.527)	-2.521*	(1.063)
%High/moderate-risk courses	-0.463	(0.347)	-0.762	(0.613)
%Moderate/low-risk courses	-0.091	(0.230)	-0.347	(0.551)
%Online courses	-0.129	(0.177)	-0.093	(0.300)
%000-level courses	-0.109	(0.367)	0.756	(0.554)
%200-level courses	-0.111	(0.273)	0.005	(0.536)

Yellow-Red Sample New and Returning Students GPA Results (continued)

%Courses retaking	-0.217	(0.251)	-0.928	(2.919)
Intercept	-9.309	(14.366)	33.508	(27.474)
<i>N</i>	478		221	
<i>R</i> -squared	0.2207		0.4946	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Because the focus subgroup was “New Student,” the following were removed from the model used for the whole-sample analyses: *Returning student with dropped courses; New student/no credit last 5 years; Returning student with withdrawals; New student/returning after 5 years; no GPA yet; GPA=2.78-3.44; GPA>3.44;* and *If returning student, all past courses passed*. To avoid issues with collinearity, these covariates were also excluded from the “Returning Student” subgroup model.

Yellow-Red Sample Female and Male Students GPA Results

Variable	Female		Male	
Success Coaching	0.140	(0.128)	-0.189	(0.155)
Aviso average model score	0.428	(42.830)	0.193	(47.097)
Aviso average model score squared	-3.962	(26.774)	1.013	(30.022)
Asian	0.630	(0.416)	-0.878	(0.519)
African American	-0.160	(0.192)	-0.480*	(0.220)
Latino	-0.170	(0.171)	-0.175	(0.240)
Native American	-0.103	(0.421)	-1.827***	(0.475)
Race missing	-0.505*	(0.248)	0.342	(0.271)
Age=21-26	0.085	(0.201)	0.335	(0.237)
Age=>27	-0.011	(0.271)	1.211**	(0.354)
AGI missing	-0.777***	(0.192)	-0.219	(0.287)
AGI>\$20736	-0.155	(0.174)	-0.410	(0.222)
Independent tax status	0.246	(0.192)	-0.455	(0.289)
Dependency tax status missing	0.314	(0.274)	-0.054	(0.325)
Math score missing	-0.356	(0.215)	0.024	(0.237)
Math score>20	-0.407	(0.440)	0.380	(0.335)
Reading placement score missing	0.250	(0.187)	-0.201	(0.238)
Reading placement score=75.1-90	0.780***	(0.178)	0.045	(0.255)
Reading placement score>90	0.578*	(0.264)	-0.274	(0.287)
No transfer credit	0.140	(0.275)	-0.211	(0.253)
Previously received free aid	-0.803***	(0.227)	-0.270	(0.292)
Returning student with drops	0.211	(0.150)	-0.316	(0.187)
New student/no credit last 5 years	-0.813	(0.756)	-0.408	(0.583)
Returning student with withdrawals	-0.615**	(0.200)	0.024	(0.228)
New student/returning after 5 years	-0.119	(0.592)	0.185	(0.515)
No GPA yet	0.229	(0.235)	-0.208	(0.267)
GPA=2.78-3.44	0.390	(0.219)	0.039	(0.229)
GPA>3.44	1.982***	(0.436)	0.413	(0.381)
If returning student, all past courses passed	0.497*	(0.196)	0.882***	(0.218)
Taking 6-9 credits	0.461	(0.234)	-0.201	(0.340)
Taking 10-11 credits	0.360	(0.316)	-0.054	(0.371)
Taking > 12 credits	0.842**	(0.296)	-0.088	(0.379)
No developmental math score	0.388	(0.197)	1.069***	(0.246)
Developmental math score=6.1-7.67	0.075	(0.196)	0.894**	(0.299)
Developmental math score>7.67	0.358	(0.277)	0.877**	(0.314)
Student not receiving free aid	0.441	(0.491)	0.998*	(0.434)
Student receiving free aid =>\$5729	0.760*	(0.310)	0.284	(0.266)

Yellow-Red Sample Female and Male Students GPA Results (continued)

Student did not received Pell	0.795	(0.533)	-0.584	(0.437)
%High-risk courses	-3.200***	(0.634)	-1.417	(0.875)
%High/moderate-risk courses	-1.113**	(0.394)	-1.083*	(0.542)
%Moderate/low-risk courses	-0.945**	(0.285)	0.106	(0.303)
%Online courses	-0.678**	(0.208)	-0.134	(0.220)
%000-level courses	0.399	(0.327)	-0.437	(0.626)
%200-level courses	0.776*	(0.315)	-0.947*	(0.412)
%Courses retaking	0.224	(0.274)	-1.358**	(0.460)
Intercept	4.477	(17.082)	1.616	(18.136)
<i>N</i>	420		279	
<i>R</i> -squared	0.3612		0.4307	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Since the model limited observation based on *Female*, the variable was not included in the model.

Appendix G

Yellow-Red Sample Full-model Logit Results for Fall-to-Spring Retention

Variable	Unweighted		Weighted		Weighted with covariates	
Success Coaching	0.379*	(0.170)	0.075	(0.293)	-0.001	(0.272)
Aviso average model score					63.384	(72.552)
Aviso average model score squared					-42.679	(46.064)
Female					0.089	(0.328)
Asian					0.311	(1.280)
African American					-0.248	(0.427)
Latino					-0.209	(0.388)
Native American					2.708	(1.436)
Race missing					0.337	(0.652)
Age=21-26					0.229	(0.411)
Age=>27					0.996	(0.658)
AGI missing					-0.912	(0.588)
AGI>\$20736					-0.148	(0.368)
Independent tax status					-0.591	(0.530)
Dependency tax status missing					0.540	(0.699)
Math score missing					-0.195	(0.428)
Math score>20					-0.003	(0.766)
Reading placement score missing					0.355	(0.440)
Reading placement score=75.1-90					1.273*	(0.492)
Reading placement score>90					0.534	(0.565)
No transfer credit					0.908	(0.529)
Previously received free aid					-0.639	(0.553)

Appendix G (continued)

Returning student with drops	0.816*	(0.395)
New student/no credit last 5 years	0.110	(1.568)
Returning student with withdrawals	-1.181**	(0.455)
New student/returning after 5 years	-0.722	(0.944)
No GPA yet	0.526	(0.514)
GPA=2.78-3.44	2.307***	(0.620)
GPA>3.44	5.256***	(1.502)
If returning student, all past courses passed	-0.052	(0.434)
Taking 6-9 credits	-0.286	(0.470)
Taking 10-11 credits	1.698*	(0.732)
Taking > 12 credits	1.447*	(0.636)
No developmental math score	0.694	(0.432)
Developmental math score=6.1-7.67	0.815	(0.471)
Developmental math score>7.67	1.149*	(0.539)
Student not receiving free aid	1.830*	(0.866)
Student receiving free aid =>\$5729	1.578**	(0.546)
Student did not received Pell	0.057	(0.893)
%High-risk courses	-4.021*	(1.672)
%High/moderate-risk courses	-1.993	(0.847)
%Moderate/low-risk courses	-0.757	(0.600)
%Online courses	-0.667	(0.397)
%000-level courses	1.374	(0.929)
%200-level courses	0.648	(0.623)
%Courses retaking	-0.941	(0.724)

Appendix G (continued)

Intercept	0.763***	(0.119)	1.067***	(0.266)	-24.369	(28.441)
N	699		699		699	
Pseudo R2	0.0061		0.0002		0.2059	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Appendix H

Yellow-Red Sample Not University Transfer Logit Results

Variable	Not University Transfer	
Success Coaching	0.546	(0.368)
Aviso average model score	49.059	(91.069)
Aviso average model score squared	-35.242	(57.537)
Female	-0.093	(0.472)
Race category 1	0.330	(0.558)
Race category 2	-0.252	(0.551)
Age=21-26	-0.287	(0.578)
Age=>27	0.300	(0.737)
AGI missing	-0.393	(0.644)
AGI>\$20736	0.244	(0.515)
Independent tax status	-0.290	(0.608)
Dependency tax status missing	-1.468	(0.892)
Math score missing	-0.237	(0.661)
Math score>20	-1.014	(1.076)
Reading placement score missing	0.226	(0.512)
Reading placement score=75.1-90	1.238*	(0.591)
Reading placement score>90	0.121	(0.828)
No transfer credit	1.772**	(0.589)
Previously received free aid	0.184	(0.655)
Returning student with drops or withdrawals	0.155	(0.553)
New student/returning no credit 5 years	-0.321	(1.430)
GPA > 2.77	1.974**	(0.736)
If returning student, all past courses passed	0.039	(0.515)
Taking 6-9 credits	-0.284	(0.645)
Taking 10-11 credits	1.411	(1.055)
Taking > 12 credits	1.970*	(0.867)
No developmental math score	1.629*	(0.658)
Developmental math score=6.1-7.67	0.114	(0.584)
Developmental math score>7.67	2.417**	(0.858)
Student not receiving free aid	1.395	(1.174)
Student receiving free aid =>\$5729	1.453	(0.750)
Student did not received Pell	1.352	(1.087)
%High-risk courses	2.405	(1.829)
%High/moderate-risk courses	-1.333	(1.061)
%Moderate/low-risk courses	-0.475	(0.710)
%Online courses	-0.919	(0.529)

Yellow-Red Sample Not University Transfer Logit Results (continued)

%000-level courses	0.965	(1.086)
%200-level courses	0.856	(0.946)
%Courses retaking	-0.716	(0.936)
Intercept	-20.593	(35.827)
<i>N</i>	414	
Pseudo <i>R</i> ²	0.2763	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The size of the university transfer subgroup was too small ($N=186$) to analyze with the logit model. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White, Asian, Native American, and Race missing*. The “Race category” variable was originally an ordinal variable provided in Aviso’s dataset. To avoid other collinearity issues, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Yellow-Red Sample Associate Degree Logit Results

Variable	Associate Degree	
Success Coaching	0.175	(0.291)
Aviso average model score	75.211	(80.944)
Aviso average model score squared	-50.886	(51.114)
Female	-0.046	(0.355)
Race category 1	-0.382	(0.474)
Race category 2	-0.272	(0.441)
Age=21-26	0.017	(0.440)
Age=>27	0.674	(0.678)
AGI missing	-0.912	(0.612)
AGI>\$20736	-0.078	(0.389)
Independent tax status	-0.490	(0.560)
Dependency tax status missing	0.400	(0.768)
Math score missing	0.190	(0.450)
Math score>20	0.267	(0.786)
Reading placement score missing	0.087	(0.471)
Reading placement score=75.1-90	1.080*	(0.508)
Reading placement score>90	0.154	(0.587)
No transfer credit	0.918	(0.550)
Previously received free aid	-0.415	(0.581)
Returning student with drops	0.802*	(0.406)
New student/no credit last 5 years	0.280	(1.907)
Returning student with withdrawals	-0.985*	(0.488)
New student/returning after 5 years	-0.279	(1.449)
No GPA yet	0.622	(0.561)
GPA=2.78-3.44	2.119***	(0.598)
GPA>3.44	8.471***	(1.463)
If returning student, all past courses passed	-0.139	(0.463)
Taking 6-9 credits	-0.169	(0.571)
Taking 10-11 credits	1.868*	(0.864)
Taking > 12 credits	1.655*	(0.744)
No developmental math score	1.102*	(0.490)
Developmental math score=6.1-7.67	0.680	(0.499)
Developmental math score>7.67	1.491*	(0.600)
Student not receiving free aid	1.617	(0.869)
Student receiving free aid =>\$5729	1.626**	(0.564)
Student did not received Pell	0.285	(0.896)
%High-risk courses	-2.734	(1.635)

Yellow-Red Sample Associate Degree Logit Results (continued)

%High/moderate-risk courses	-1.922*	(0.909)
%Moderate/low-risk courses	-0.909	(0.666)
%Online courses	-0.559	(0.435)
%000-level courses	1.325	(0.942)
%200-level courses	0.850	(0.703)
%Courses retaking	-0.947	(0.817)
Intercept	-29.293	(31.898)
N	600	
Pseudo R2	0.2179	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The size of the non-associate degree subgroup was too small ($N=99$) to analyze with the logit model. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White, Asian, Native American*, and *Race missing*. The “Race category” variable was originally an ordinal variable provided in Aviso’s dataset.

Yellow-Red Sample Online Course Percentage Logit Results

Variable	Online Courses>=>20%		Online Courses<20%	
Success Coaching	0.347	(0.405)	-0.133	(0.449)
Aviso average model score	15.156	(105.427)	166.883	(144.475)
Aviso average model score squared	-9.768	(66.817)	-110.083	(92.959)
Female	-0.075	(0.457)	0.440	(0.542)
Race category 1	0.471	(0.534)	-1.047	(0.699)
Race category 2	-0.482	(0.600)	-0.335	(0.539)
Age=21-26	0.013	(0.598)	-0.336	(0.535)
Age=>27	0.090	(0.797)	0.913	(1.251)
AGI missing	-1.058	(0.800)	-0.501	(0.753)
AGI>\$20736	-1.147*	(0.510)	1.091	(0.613)
Independent tax status	-0.740	(0.612)	0.616	(0.778)
Dependency tax status missing	0.116	(1.041)	1.033	(0.817)
Math score missing	-0.356	(0.587)	0.760	(0.647)
Math score>20	-0.605	(0.893)	2.385	(1.375)
Reading placement score missing	-0.177	(0.556)	0.848	(0.580)
Reading placement score=75.1-90	1.366*	(0.687)	1.000	(0.634)
Reading placement score>90	0.357	(0.825)	-0.324	(0.748)
No transfer credit	1.192*	(0.567)	0.122	(0.842)
Previously received free aid	-0.214	(0.690)	-0.815	(0.739)
Returning student with drops or withdrawals	0.099	(0.549)	-1.018	(0.679)
New student/returning no credit 5 years	0.050	(1.649)	-0.711	(1.023)
GPA>2.77	2.048**	(0.731)	2.203*	(0.862)
If returning student, all past courses passed	-0.035	(0.591)	0.279	(0.626)
Taking 6-9 credits	-0.011	(0.689)	-0.655	(0.739)
Taking 10-11 credits	1.530	(1.027)	2.307*	(1.122)
Taking > 12 credits	1.113	(0.831)	2.742**	(0.961)
No developmental math score	0.904	(0.619)	-0.006	(0.620)
Developmental math score=6.1-7.67	1.421*	(0.652)	-0.009	(0.715)
Developmental math score>7.67	2.884**	(0.971)	-0.908	(0.986)
Student not receiving free aid	2.118	(1.277)	2.278	(4.864)
Student receiving free aid =>\$5729	0.728	(0.713)	3.304***	(0.806)
Student did not received Pell	-0.489	(1.288)	0.548	(4.832)
%High-risk courses	-0.439	(1.972)	-4.533*	(1.966)
%High/moderate-risk courses	0.658	(1.236)	-3.610*	(1.521)
%Moderate/low-risk courses	0.154	(0.736)	-1.014	(0.840)
%000-level courses	0.340	(1.212)	2.460*	(1.082)
%200-level courses	-0.934	(0.879)	1.096	(0.946)
%Courses retaking	-0.454	(1.039)	-2.274**	(0.866)

Yellow-Red Sample Online Course Percentage Logit Results (continued)

Intercept	-7.313	(41.278)	-64.822	(55.807)
<i>N</i>	404		295	
<i>R</i> -squared	0.2613		0.3486	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The covariate %*Online courses* was excluded from the model since it was the limiting variable for the subgroup analysis. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White, Asian, Native American, and Race missing*. The “Race category” variable was originally an ordinal variable provided in Aviso’s dataset. To avoid other collinearity issues, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.

Yellow-Red Sample New and Returning Students Logit Results

Variable	New		Returning	
Success Coaching	-0.031	(0.327)	0.145	(0.581)
Aviso average model score	-34.250	(91.104)	187.727	(199.350)
Aviso average model score squared	23.256	(57.130)	-118.604	(129.129)
Female	-0.056	(0.389)	0.799	(0.678)
Race category 1	-0.576	(0.515)	-1.181	(0.828)
Race category 2	0.042	(0.458)	-0.836	(0.678)
Age=21-26	0.402	(0.454)	-0.510	(1.009)
Age=>27	1.590	(0.700)	-1.449	(1.148)
AGI missing	-0.215	(0.599)	-1.257	(0.914)
AGI>\$20736	-0.902	(0.470)	0.320	(0.914)
Independent tax status	-0.770	(0.535)	0.503	(0.921)
Dependency tax status missing	-1.224	(0.811)	1.502	(1.172)
Math score missing	0.407	(0.551)	-1.206	(0.779)
Math score>20	0.486	(0.755)	0.338	(1.698)
Reading placement score missing	1.056	(0.622)	-15.038***	(2.373)
Reading placement score =<75	0.684	(0.604)	-16.120***	(2.583)
Reading placement score=75.1-90	1.848**	(0.630)	-15.608***	(2.676)
No transfer credit	1.359*	(0.601)	-0.183	(1.524)
Previously received free aid	0.636	(0.573)	-4.302*	(1.786)
Taking 6-9 credits	-0.484	(0.665)	-0.374	(0.952)
Taking 10-11 credits	1.640	(0.921)	1.509	(1.180)
Taking > 12 credits	1.308	(0.865)	1.001	(1.129)
No developmental math score	0.525	(0.523)	0.940	(0.772)
Developmental math score=6.1-7.67	1.545*	(0.691)	0.194	(0.641)
Developmental math score>7.67	0.403	(0.595)	1.649	(1.020)
Student not receiving free aid	2.570**	(0.860)	-1.749	(1.959)
Student receiving free aid =>\$5729	0.757	(0.709)	2.147	(1.179)
Student did not received Pell	-1.354	(0.900)	3.800	(2.280)
%High-risk courses	2.676	(1.903)	-8.889**	(2.877)
%High/moderate-risk courses	-0.714	(0.876)	-3.279	(1.826)
%Moderate/low-risk courses	-0.084	(0.674)	-2.021	(1.362)
%Online courses	0.569	(0.509)	-1.658	(0.855)
%000-level courses	0.312	(0.883)	1.215	(1.349)
%200-level courses	0.989	(0.731)	-1.052	(1.526)
%Courses retaking	-1.140	(0.739)	-7.169	(5.186)
Intercept	9.305	(36.001)	-51.771	(77.349)

Yellow-Red Sample New and Returning Students Logit Results (continued)

<i>N</i>	478	221
Pseudo <i>R</i> ²	0.2204	0.3492

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Because the focus subgroup was “New Student,” the following were removed from the model used for the whole-sample analyses: *Returning student with dropped courses*; *New student/no credit last 5 years*; *Returning student with withdrawals*; *New student/returning after 5 years*; *no GPA yet*; *GPA=2.78-3.44*; *GPA>3.44*; and *If returning student, all past courses passed*. To avoid issues with collinearity, these covariates were also excluded from the “Returning Student” subgroup model. Since the ethnicity dummy variables cause collinearity issues when using the whole-sample model, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White, Asian, Native American, and Race missing*. The “Race category” variable was originally an ordinal variable provided in Aviso’s dataset.

Yellow-Red Sample Female and Male Students Logit Results

Variable	Female		Male	
Success Coaching	0.379	(0.365)	-0.635	(0.480)
Aviso average model score	-2.782	(93.939)	305.443	(158.081)
Aviso average model score squared	-0.020	(59.191)	-190.146	(100.709)
Race category 1	0.650	(0.538)	-0.685	(0.640)
Race category 2	-0.296	(0.490)	-0.967	(0.679)
Age=21-26	-0.119	(0.529)	-0.808	(0.804)
Age=>27	0.097	(0.766)	0.225	(1.189)
AGI missing	-0.158	(0.601)	-1.281	(1.057)
AGI>\$20736	0.003	(0.485)	-1.157	(0.782)
Independent tax status	-0.374	(0.616)	-0.108	(1.041)
Dependency tax status missing	-1.039	(0.842)	1.455	(1.195)
Math score missing	-0.147	(0.618)	1.186	(0.850)
Math score>20	-1.937	(1.078)	5.102**	(1.637)
Reading placement score missing	0.460	(0.587)	-1.401	(1.004)
Reading placement score=75.1-90	1.393*	(0.647)	-0.129	(0.830)
Reading placement score>90	-0.056	(0.867)	-2.072*	(1.005)
No transfer credit	1.371*	(0.671)	0.235	(0.901)
Previously received free aid	-0.586	(0.657)	0.736	(0.788)
Returning student with drops or withdrawals	0.340	(0.548)	0.032	(0.706)
New student/returning no credit 5 years	0.478	(1.362)	-1.453	(1.359)
No GPA yet	0.361	(0.661)	1.399	(1.109)
GPA=2.78-3.44	1.449*	(0.613)	4.536***	(1.238)
GPA>3.44	7.052***	(1.603)	4.228	(2.277)
If returning student, all past courses passed	-0.434	(0.521)	-0.612	(0.953)
Taking 6-9 credits	-0.213	(0.624)	-1.241	(0.880)
Taking 10-11 credits	1.830*	(0.924)	1.681	(1.162)
Taking > 12 credits	1.417	(0.823)	1.136	(0.895)
No developmental math score	-0.187	(0.531)	1.224	(0.833)
Developmental math score=6.1-7.67	0.627	(0.567)	1.448	(1.063)
Developmental math score>7.67	1.042	(0.843)	1.175	(0.873)
Student not receiving free aid	1.826	(0.935)	5.698***	(1.534)
Student receiving free aid =>\$5729	0.784	(0.646)	2.121*	(0.909)
Student did not received Pell	0.016	(0.955)	-4.056**	(1.478)
%High-risk courses	-0.994	(1.730)	-3.782	(3.277)
%High/moderate-risk courses	-0.288	(1.040)	-5.861**	(2.057)

Yellow-Red Sample Female and Male Students Logit Results (continued)

%Moderate/low-risk courses	0.117	(0.700)	-0.546	(0.815)
%Online courses	-0.624	(0.538)	0.764	(0.754)
%000-level courses	0.462	(0.951)	3.312	(1.796)
%200-level courses	1.046	(0.897)	-0.419	(0.949)
%Courses retaking	-0.086	(0.878)	-4.306**	(1.312)
Intercept	0.470	(37.009)	-122.827*	(62.252)
<i>N</i>	420		279	
Pseudo <i>R</i> ²	0.2534		0.3806	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Since the model limited observation based on *Female*, the variable was not included in the model. To avoid collinearity, *Race Category 1* replaced *African American*, and *Race category 2* replaced *Latino*. The reference variable *Race category 1* replaced *White, Asian, Native American*, and *Race missing*. The “Race category” variable was originally an ordinal variable provided in *Aviso’s* dataset. Likewise, *Returning student with drops or withdrawals*, as a combined variable, replaced covariates *Returning student with dropped courses* and *Returning student with withdrawals*, and *New student/returning no credit 5 years* replaced *New student/no credit last 5 years* and *New student/returning after 5 years*.