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Adaptive Analytics: It’s About Time

Charles Dziuban
University of Central Florida, Charles.Dziuban@ucf.edu

Colm Howlin
Realizeit, colm.howlin@realizeitlearning.com

Patsy Moskal
University of Central Florida, patsy.moskal@ucf.edu

Tammy Muhs
University of Central Florida, tammy.muhs@ucf.edu

Connie Johnson
Colorado Technical University, cjohnson@coloradotech.edu

See next page for additional authors

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Authors

Charles Dziuban, Colm Howlin, Patsy Moskal, Tammy Muhs, Connie Johnson, Rachel Griffin, and Carissa Hamilton

ADAPTIVE ANALYTICS: IT'S ABOUT TIME

Charles Dziuban, *University of Central Florida*
Colm Howlin, *Realizeit*
Patsy Moskal, *University of Central Florida*
Tammy Muhs, *University of Central Florida*
Connie Johnson, C*olorado Technical University*
Rachel Griffin, *University of Central Florida*
Carissa Hamilton, *University of Central Florida*

INTRODUCTION

The United States offers post-secondary learning opportunities that rival or surpass those of any other country in the world. The educational landscape offers affordances such as vocational-technical training, community college, public and private colleges and universities, for profit institutions and a host of other higher education opportunities. Truly motivated high school graduates in this country have many options to obtain a skill, certificate or degree despite the opportunity costs involved. Furthermore, higher education institutions are making extensive efforts to ensure college success. Some of these initiatives include: time-shortened degree programs, dual enrollment, experiential course credit, flexible attendance policies, credit for military training, learn while you work, and many other adaptations that remove or minimize the "you must be on campus full time" requirement.

Perhaps the most innovative transformation belongs to the online learning environment which continually develops new formats such as: fully online, blended, flipped, MOOCs and adaptive learning. These initiatives respond to the complex lifestyles of students who must manage increasing ambiguity, ambivalence, economic demands and uncertainty placed on them by our technology-mediated society. Much of this innovation appears to be motivated by our increasing understanding of the value-add that comes from certificate or degree attainment supporting a healthier society and reducing economic inequality. By building human capital we reduce crime rates, stabilize family structures, produce more civic minded citizens, and raise those living in poverty into the middle class (Becker, 2009). Depending on the discipline in which a student earns a college degree, the degree can be worth an average of one million dollars in additional lifetime income over a high school diploma; graduate degrees are worth an additional million dollars (Carnevale, Cheah, & Rose, 2011).

Despite these innovations, the educational system in the United States faces many challenges that mitigate much of what we hope to accomplish. For instance, students living in the bottom economic quartile in this country -- those anyway who do not receive additional support -- have an approximate 10% chance of obtaining a college degree; the odds against them are 9:1: however, students living in the top economic quartile in this country are 90% sure of college graduation; their odds of success are 9:1 (Sherman, 2015). These data regarding an unacceptable inequality, sometimes referred to as the Mathew effect (Saleh, & Sanders, 2014), confirm the *prosperity advantage* in our educational system. The economics of attending college compound the impacts of disproportionate opportunity. Burgeoning loans are crippling students with long term pay back responsibility. Unfortunately, those living in poverty who can least afford this kind of financial support have to borrow the most (Mitchell & Hackman, 2019). This creates the scarcity phenomenon described by Mullainathan and Shafir (2013) in which students living in poverty are overwhelmed by the many circumstances they have to juggle in their lives. They may be holding down two part-time jobs such that full course loads are not possible. Health care becomes a significant financial problem in addition to the costs of tuition, textbooks, transportation, and additional expenses. Most often these students are forced to borrow money because, unfortunately, they simply do not get the information about how to apply for scholarships. The demands and stresses in their lives create a fragile balancing act. If a student fails in the attempt to respond to any one of these scarcity demands and stresses, that student's whole life structure can come tumbling down. Mullainathan and Shafir (2013) describe it this way:

> *What happens when, loaded and depleted, a client misses a class? What happens when her mind wanders in class? The next class becomes a lot harder. Miss one or two more classes and dropping out becomes the natural outcome, perhaps even the best option, as she really no longer understands much of what is being discussed in the class. A rigid curriculum – each class building on the previous - is not a forgiving setting for students whose bandwidth is overloaded. Miss a class here and there and our student has started a slide from which she is unlikely to recover. (p. 170)*
> *Linear classes that must not be missed can work well for the full-time student; they do not make sense for the juggling poor. (p. 171)*

However, scarcity appears in circumstances other than underserved neighborhoods. Consider working adults who feel pressures from their employers to obtain additional skills and academic credentials in order to progress or receive promotions. In contemporary society it is not feasible for them to take a hiatus from their work and go back to school, full time. Most face arduous time demands in the workplace, often compounded with travel requirements that, in many cases, interfere with family obligations. These working professionals have no flexibility in their lives so even taking courses online over a 16-week semester is simply not feasible. They need a compressed educational agenda. For these individuals, time is a scarce commodity.

Higher education is not immune to scarcity. For instance, faculty and administrators must cope with time demands that come from burgeoning requirements for communication, interaction, research, publication, community service, teaching, and many other aspects of the academic life. Therefore, most academics do what Mullainathan and Shafir (2013) label tunneling. They exclude other demands and concentrate on the thing that must be completed immediately, abandoning all other responsibilities. As Brene' Brown (2012) found, exhaustion is becoming a status symbol in our society.

There is an additional problem in higher education that prevents capable students from obtaining a degree. Anthony Jack (2019) in his book *The Privileged Poor* documents how doubly disadvantaged students (those who have not received scholarships to preparatory schools primarily serving the wealthy) face a culture that unknowingly and unintentionally excludes them from the opportunities of higher education. His research shows that elite schools especially, although making every effort to give students from underrepresented neighborhoods access, force them into a culture that denies them inclusion. The Mathew effect tells these students that they don't really have a place in what Jack calls "Renowned College." Wealthy students operate with a sense of agency and empowerment. Poor students feel isolated, alone, disenfranchised and frustrated; experiences that greatly diminish their chances of success. In many instances a wonderful opportunity is lost.

THE STUDY

Given these simultaneous opportunities and challenges in American higher education, two innovations offer promise: adaptive learning and learning analytics. In this study we investigate their interaction for helping students succeed in college Algebra, a course that continues to be a challenge for students. We investigate the interaction of adaptive learning and learning analytics at two contextually different institutions whose members have worked in partnership with the research unit of their common adaptive learning platform partner, Realizeit: the University of Central Florida, a large metropolitan institution and Colorado Technical University, a primarily online for-profit institution. The cooperative partnership closely resembles the model proposed by Feldstein's Empirical Educator initiative in which universities and technology providers contribute intellectual resources to identify and evaluate effective practices in education (Feldstein, 2018). Exploring our own partnership in this work, we address the question of whether or not adaptive learning, with its variable time learning framework, provides a platform for finding actionable analytics variables that predict student success in Algebra and that also are responsive to instruction. The phrase "responsive to instruction" refers to our hope that, if we were able to identify actionable analytics variables that correlate with positive learning outcomes, we also would be able to identify possibilities for teaching curriculum designers and instructors how to manipulate these analytics variables to engineer student success.

Adaptive Learning and Learning analytics

Adaptive Learning

Throughout the past several years, the implementation of adaptive learning has developed rapidly. However, in spite of significant funding by several national organizations (Bill & Melinda Gates Foundation, 2014; Association of Public & Land-Grant Universities, 2016; Online Learning Consortium, 2016), research results have been mixed with a 2016 meta-analysis (Yarnell, Means & Wetzel, 2016) finding only limited improvement in outcomes at 4 of 15 institutions that received funding from the Bill & Melinda Gates Foundation. Much of this research is institution centric, focusing on such things as student experience and perception of adaptive technology, its integration with mobile learning, or the efficacy of using these tools within an online or flipped classroom.

Nakic, Granic & Glavinic (2015) argued that adaptive learning can facilitate improvements in student retention, satisfaction, and the achievement of student outcomes. Dziuban, Moskal, Johnson and Evans (2016) found positive reactions to adaptive learning technology among students from two different student populations, traditional 18-22 year old students attending the University of Central Florida and adult students with an average age between 30–39 attending Colorado Technical University. Students reported that adaptive learning personalized their instruction, helping them learn the material better and increasing their levels of engagement (Dziuban, Moskal, Cassisi & Fawcett, 2016). Additionally, adaptive learning allowed the student and the faculty members to shift time to learning areas that may not get addressed in a traditional classroom setting (Dziuban, Moskal & Hartman, 2016).

Johnson and Zone (2018) and Cavanagh, Chen, Lahcen and Paradiso, (2020) discussed the importance of faculty engagement and training as fundamental to the utilization and scaling of adaptive learning technology to support data-driven decisions. Development challenges included what faculty perceived as the daunting number of components, patterns and sequences required to adapt course content meaningfully (Panicker, Kumar, Joohn & Srinivasam, 2018). Adaptive learning design can vary based upon content. For instance, courses with a linear structure, characterized by having one concept following sequentially after another with little hierarchical structure are easier to adapt (Cai, 2018).

LEARNING ANALYTICS

With today's advanced modeling and computing expertise, many universities are investigating learning analytics in an attempt to solve the higher education challenge of improving student success and retention. As students' progress through the college experience, models are formed using analytics to "predict" which students might be at risk. In fact, "technologies for improving analysis of student data" was listed as one of the top 10 strategic technologies in the 2019 EDUCAUSE Horizon Report as were "learning analytics for student success (institutional level)," highlighting the influence of these approaches today (Alexander et al., 2019).

The examination of the learning analytics national landscape conducted by Association for Institutional Research (AIR), NASPA-Student Affairs Administrators in Higher Education, and EDUCAUSE found that 91% of institutions are investing in analytic studies that are primarily descriptive. These efforts focus on describing the student environment and identifying high risk courses, although 89% of institutions were engaged in some predictive studies that examined factors influencing retention, persistence, and student GPA. Larger institutions are more likely to engage in such research. Such institutions use data-informed models to create early alerts, primarily for academic and faculty advisors (Parnell, Jones, Wesaw, & Brooks, 2018). Initiatives such as the Bill & Melinda Gates funded and EDUCAUSE led *Integrated Planning and Advising for Student Success (iPASS)* developed guidance and roadmaps for institutions by providing financial, technical, and change-management support to these colleges and universities ("Integrated Planning and Advising," 2013).

Much of the research in learning analytics has focused on work utilizing big data methods to help identify effective models that have a high degree of accuracy for predicting those students who are most likely to be at risk for not completing college (Moskal, Cavanagh, Wang & Zhu, 2020; Simanca, González Crespo, Rodríguez-Baena & Burgos, 2019; Smith, Lange & Huston, 2012; Wladis, Hachey & Conway, 2014; Miguéis, Freitas, Garcia & Silva, 2018). Algorithms have varied widely based on educational context, data at hand, and analyses used, but most have incorporated university data captured and stored in the student information system (SIS), forming the topics of conferences and journals devoted to learning analytics (Society for Learning Analytics Research, 2020; Moskal, Cavanagh, Wang & Zhu, 2020; Journal of Learning Analytics, 2020).

This learning analytics research is often institutionally specific examining single-use initiatives for prediction of students at-risk; such research can be difficult to scale and transport beyond the home institution. As a result, universities that incorporate these "big data" initiatives into their plans often rely on outside platforms such as those available from the Education Advisory Board (EAB) to provide the predictive results in easy-to-use dashboard form Georgia State

University is one such school where the Graduation and Progression Success (GPS) initiative provided an early warning system that updated students' grades and records nightly, pushing notifications to advisors in cases in which a student was flagged as being at risk. The initiative increased graduation rates by 10%, decreasing the time to degree, closing the graduation gap for low-income, first generation, and minority students; the initiative also increased STEM major success (Kamenetz, 2016; Bailey, Vaduganathan, Henry, Laverdiere, & Jacobson, 2019). The University of South Florida increased its 6-year graduation rate from 48% to 73% from 2008-2018 by integrating learning analytics into a cross-functional plan to address persistence and graduation rates (Dosal, 2019). However, because these initiatives have incorporated learning analytics along with a suite of other university-wide tools and initiatives to address student success, it can be difficult to determine the direct gains due specifically to the learning analytics tools.

Politico referred to this use of big data as the "Moneyball" solution for higher education (Hefling, 2019). Eduventures reported that these efforts have developed into a $500 million market for the learning analytics industry, with colleges typically paying hundreds of thousands of dollars to the more than 30 for-profit companies that sell learning analytics tools (Barshay & Aslanian, 2019).

We have found an alternative approach through our research using Realizeit, an approach that bridges the worlds of adaptive learning, learning analytics, and institutional context. Because adaptive learning platforms can generate detailed and real-time data regarding student behaviors, engagement, and performance in a course, these platforms can provide a rich source of information that can help "predict" students' levels of success. The challenge is predicting students' performance early enough to intervene prior to students having too little opportunity to correct their behaviors.

THE PARTNERSHIP

The University of Central Florida (UCF) is one of 12 universities in Florida's State University System. Over 69,000 students attended during the Fall 2019 semester. UCF is a diverse, Hispanic serving institution with 50% first time in college students, 48% minority enrollment and an average age of 23.7 (UCF Facts, 2019).

Colorado Technical University (CTU) is a for-profit university providing industry-relevant programs to approximately 25,000 students. Students within CTU's diverse student body are mostly online learners with an average age of 36.

Both UCF and CTU have extensive support for faculty members who are utilizing adaptive learning, including instructional designers who help faculty focus on the pedagogy for utilizing various technologies. Both universities use Realizeit, with CTU beginning in Fall 2012 and UCF beginning in Fall 2014.

Realizeit is an adaptive platform that allows existing content to be integrated within, or new content to be created within the framework of the platform. The platform can adapt to incorporate distinct characteristics of each instructor, course, or institution's instructional design schema, an outcome the platform achieves by separating content from curriculum (Howlin & Lynch, 2014). Realizeit creates a map (the Curriculum Prerequisite Network) that provides students many alternative pathways to move through the course concepts based on students' real-time knowledge.

How College Algebra Became Adaptive At UCF

College Algebra at the University of Central Florida (UCF) requires students to sit for a mathematics placement examination. Should they not meet the department requirement, a noncredit intermediate Algebra (IA) course becomes prerequisite. Despite that precondition, at the time of this data analysis, nonsuccess in Algebra (a grade of less than C or better) for students enrolling directly or through IA was approximately 41%. Students' odds of success are favorable but only marginally (about 1.4:1). Therefore, improving the potential for success motivated UCF to adopt the Realizeit adaptive learning platform as the structural foundation for the course.

Realizeit is content agnostic; therefore design within Realizeit requires that course learning materials be created or imported from previously published works. UCF's decision to create the adaptive college Algebra course content provided the institution with an opportunity to personalize the learning materials in a manner that addressed the common student complaints regarding textbook readability, course relevance, and rising textbook costs. The course was designed to incorporate objectives-based learning, alternate content for each of the lessons, and procedurally generated (algorithmic) questions. These course characteristics, along with the adaptive features of the Realizeit platform, collectively fulfil the UCF Adaptive Learning Design Framework (Figure 1).

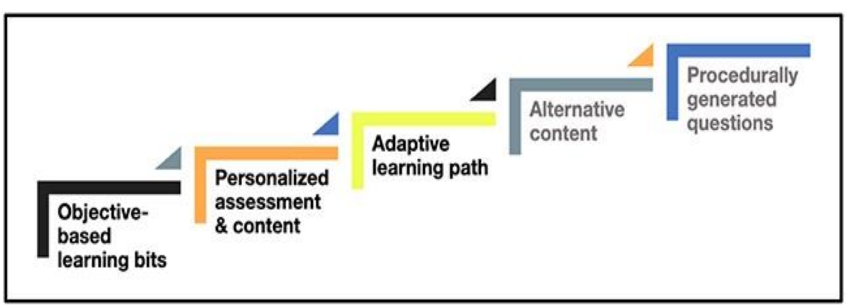


Figure 1. The UCF Adaptive Learning Design Framework

When creating the materials for college Algebra, UCF faculty, instructional designers and support staff broke down each course objective to a consistent granular level to form the associated learning bits (lessons). For example, *operations on functions*, one of the course topics required as a mandate imposed by the Florida State University System , was organized into lessons on finding the sum of functions, difference of functions, product of functions, quotient of functions, and composition of functions. Each lesson was designed to take between 20 and 30 minutes; each lesson was followed by a short formative assessment (check of understanding). In an effort to make the content understandable, course designers insured that the lesson vernacular was stated simply, and that pop-ups were embedded within each lesson to provide vocabulary definitions, mathematical properties, and formulas, when appropriate.

At the start of each assignment, students were called upon to complete a set of targeted questions (determine knowledge) that represented the objective-based lessons contained in the assignment. Based on the results of the answered questions, the student settings, and their previous work, the adaptive platform delivered personalized content and assessments to the individual student. While personalized assessment and content is often based on the results of pretest(s) and/or graded assessment(s) (Essa, 2016), the level of personalization in the UCF college Algebra course is unique because the content is personalized to UCF as well as to the student. Examples unique to UCF were mentions of notable locations, events, and programs specific to the University in the lesson examples and exercises. Because UCF has a diverse student population, name banks were used in examples and exercises that proportionally were representative of student demographics and gender were used. To address student concerns regarding course relevance, the application problems (word problems) included in practice exercises and assessments were personalized to the individual student's program of study. This was accomplished by a two part process. During the question build, nine versions of each application problem were created. The mathematics were consistent across the nine versions, but each of the versions were tailored to have a scenario representative of each of the nine identified programs of study (Arts & Humanities, Business Administration, Education & Human Performance, Engineering & Computer Science, Natural Sciences, Nursing & Healthcare, Hospitality Management, Social Sciences, and Public Affairs). The second part of the process required each student to identify with one of the nine programs of study in their personalized settings. When the student was delivered an application problem, the scenario of the problem was related to that student's identified program of study. In a sense, the result was a sense of increased value-add, since the context presented to each student related the content of the mathematical problem to the student's planned future career.

Students enrolling in college Algebra at UCF have varying levels of understanding and different knowledge sets. In any given class, some students need only a quick review of the learning objective content while others benefit from a full review of prerequisite material prior to attempting the associated content. The adaptive learning pathway includes prerequisite learning materials and an acceleration or remediation capability that adapts to students' knowledge level. Utilizing an accelerated timeline, students were able to complete multiple courses within one semester thereby reducing time to graduation. The platform also provided learning analytics while recommending personalized interventions that the instructor could review at the course, lesson, and student level.

When creating the lessons, designers included alternative adaptive content presentation types (text, pencast, and video). Students were delivered the initial presentation type based on learning performance and learning characteristics but also were provided the option to request an additional presentation, if desired. Given that some students repeated a lesson multiple times, the learning content was designed to be algorithmic.

The last of the five features included in the course were procedurally generated questions. Algorithmic, worked-out examples were built to include every step of a problem solution, with associated explanations. Similar algorithmic examples were created by removing the trivial steps and then providing associated explanations. The adaptive platform used preset conditions to deliver very detailed, step-by-step, worked-out examples to the struggling student, in hopes of preventing at-risk students from becoming lost, whereas the platform delivers to the stronger, higher performing students a similar example with the trivial steps and explanations removed.

The Search at UCF: Actionable Variables

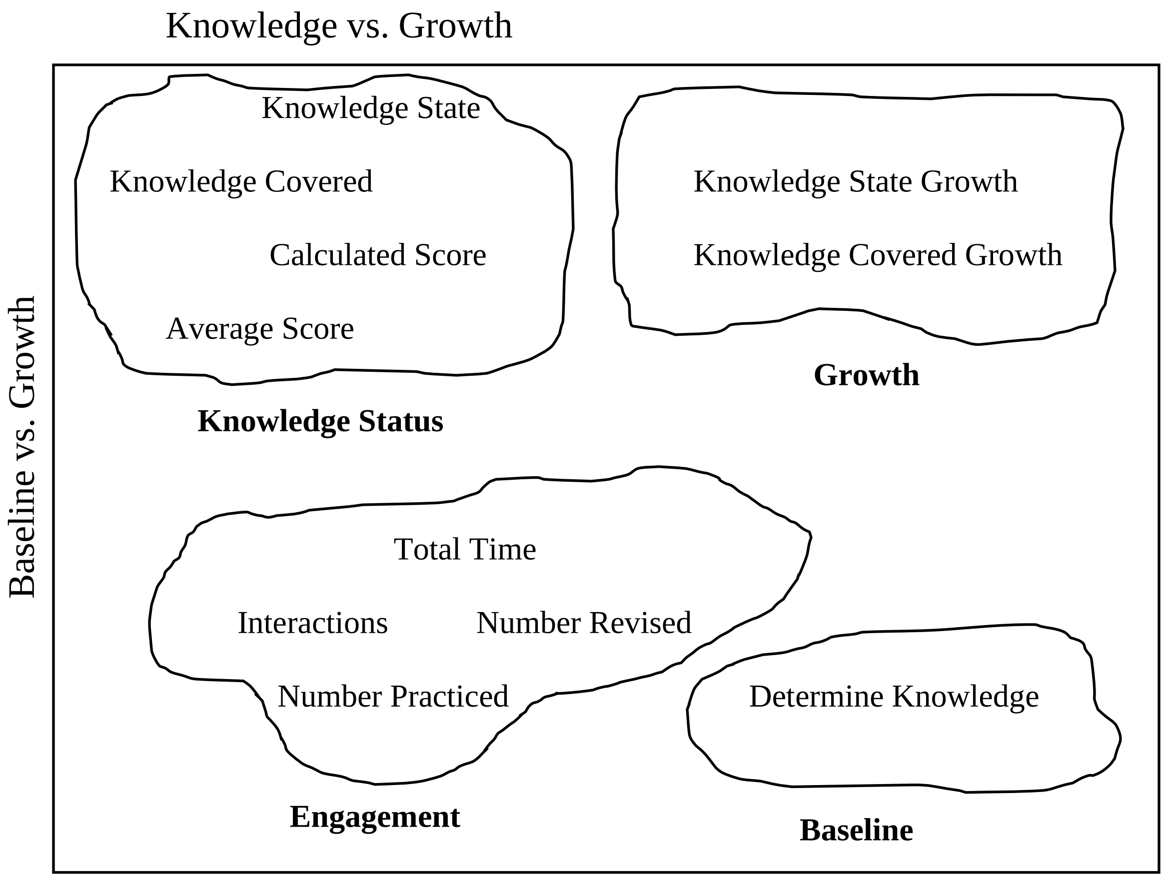
Realizeit assembles many student performance and engagement indicators 'under the hood' and makes them freely available to clients. Because the data are uniformly collected, verified, and scaled in a readily usable manner, organizations such as the Research Initiative for Teaching Effectiveness (RITE) at UCF have experienced a cooperative advantage when in engaging in developing effective learning analytics models. The objective of this study was to find through use of the Realizeit suite the most effective and actionable variables for predicting and facilitating student success in college Algebra. The indices used for modeling development are defined in Table 1.

Table 1. Realizeit Metrics - Explanation of Variables

Variable	Explanation
Knowledge State (KS)	A measure of student ability. The mean level of mastery that the students have shown on topics they have studied.
Knowledge Covered (KC)	A measure of student progress. The mean completion state of each of the course objectives.
Calculated (CA)	An institution-defined combination of several metrics, mainly KS and KC, used to assign a grade to students.
Average Score (AS)	The mean result across all learning, revision, practice, and assessment activities.
Determine Knowledge (DK)	The percentage objectives on which the student completed a Determine Knowledge operation.
Knowledge State Growth (KSG)	The extent by which a student's KS has changed from the start of the course. Can be positive, negative, or zero.
Knowledge Covered Growth (KCG)	The extent by which a student's KC has changed from the start of the course. Can be positive or zero.
Interactions (IN)	The engagement level of the instructor(s) with the student. The total number of interactions.
Total Time (TT)	The total time spent on non-assessment activities started by the student.
Number Revise (NR)	The total number of node-level activities that are classified as revision.
Number Practice (NP)	The total number of objective-level practice activities.

The first step in the modeling development process was to configure the relationship among the eleven Realizeit indices in a scaled visual space using the multidimensional scaling process (Borg, Groenen, & Mair, 2018). This approach facilitates interpretation of viable latent clusters, their relationships, and how this configuration ___ might inform further procedures.

The results of that analysis are presented in Figure 2.



$R^2 = .98$
Stress = .003

Figure 2. Smallest Space Configuration of Realizeit Indices

For the two-dimensional solution, one cluster (upper left) of variables reflected knowledge acquired while another configuration (upper right) depicted student growth. A third group of indices (center position) assessed student engagement with the learning platform. The single variable “determine knowledge” (lower right) measured students’ baseline standing. The configuration produced low stress (.003) on the system and a high squared multiple correlation (.98), meaning that the two-dimensional portrayal produced a close approximation to the ordered pairwise Euclidian distances in the entire variable set. The horizontal dimension illustrated the counterpoised relationship between acquired knowledge and growth. The vertical dimension demonstrated a similar oppositional relationship between prior status (determine knowledge) and growth as well. The engagement variables were located equidistant from the achievement and growth clusters as well, being equidistant from the baseline status of the students, impacting each to a similar degree. This scaling validated the measurement proposition that pretests are negatively related to gain scores and that students entering the course at the highest levels gain the least (Harris, 1962). This solution was initially encouraging because it suggested that students requiring the most predictive analytic assistance (low pretest and least knowledge acquired) might have the most to gain. Furthermore, this procedure identified the possible influencing variables independently from other considerations such as academic history. However, because research suggests that grade point average exerts a strong mediating influence on these procedures (Moskal, Cavanagh, Wang, & Zhu, 2020). Therefore, UCF grade point average was included within subsequent analysis procedures.

THE NEXT STEP: A SUGGESTED MODEL

The study continued with a two-level procedure designed to identify which of the Realizeit indices mediated by GPA best predicted student success and to obtain some indication of the predictive accuracy of the Realizit indices. The first step incorporated classification and regression trees (CRT), (Breiman, Friedman, Olshen, & Stone, 1984), a data-mining technique that pinpoints classification rules for identifying which variables best predict success. To deal with missing values, the user does not have to impute values because decision trees have built-in mechanisms, such as floating category approaches. Decision trees are excellent methods for studying problems such as the problem under considering because decision trees determine which variables do the "prediction heavy lifting" for success.

The follow-up analysis used the variables identified in the decision tree process in a logistic regression for dichotomous (binary) success in which one or more of the predictors are nominal, ordinal, interval or ratio-level independent variables. This was a screening process intended to give some direction for further development of the predictive models. The CRT procedure identified three variables that were most effective at predicting success in college Algebra at UCF:

- Grade Point Average (GPA)
- Total Number of Items Revised (Number Revised)
- Total Time Spent in the Course (Total Time)

Those three variables had an overall prediction accuracy rate of 77%. Using those three indices in the logistic regression model yielded a 77% prediction accuracy as well (Osborne, 2014). Therefore, GPA, revision, and total time form the foundation for this study. However, in order to build more effective classification models, the three identified variables were converted to quartiles so that the gain for analytic cohorts might be more accurately identified. In addition, this process permitted a test of greatest predicted gain for the lowest performing students versus those that demonstrated an initially high achievement level. We sought to determine if what we developed would help those in most need by improving their odds of success.

Table 2. Algebra Success by GPA, Total Time and Number Revised Quartiles

	Q1	Q2*	Q3*	Q4
GPA	26%	59%	63%	88%
Total Time	29%	61%	64%	78%
Number Revised	17%	64%	71%	78%

*Q2-Q3 N.S. for all three variables.

Table 2 presents the success rates in college Algebra (independently) for the GPA, Total Time and Revision quartiles. The patterns appear similar for all three indices. Quartile one achieves significantly lower (p=.001) success rates. Bonferroni pairwise post hoc comparisons identified non-significant contrasts. Cast in odds ratio context, the odds of a student in GPA Q1 not succeeding is almost 3:1 where conversely, a student in the top quartile has a 7:1 chance of succeeding. Total time conveys the same story: students in Q1 had 2.4:1 odds of nonsuccess but students in Q4 had a 3.5:1 chance of success. Number Revised follows similarly. In Q1, students had 5:1 odds of nonsuccess, while those in Q4 enjoyed a 5:1 chance of succeeding. The reader should remember that the impact of these indices was assessed in isolation. Their interaction was not considered; rather, analyzing them independently showed the dominant impact of the external variable GPA on student success.

Using the variables identified in the screening process, the authors used CRT to develop a set of predictive rules for determining the likelihood of nonsuccess in the college Algebra course. Noting the strong influence of GPA, GPA was used a mediator throughout the process. The results of those analyses are presented in Tables 3 through 6. Table 3 depicts the decision rule that emerged with all three variables as predictors, confirming the strong influence of GPA, with the percent of non-success independent of each rule included in the table heading.

Table 3. Nonsuccess in UCF College Algebra (41%)

	Q1	Q2	Q3	Q4
If				
Number Revised		●	●	●
GPA				●
Then				
Nonsuccess= 7%	n=495			

Given that the general non-success rate was 41%, the rule indicates that if students are in Q2 through Q4 for revision and Q4 for GPA, their chance of nonsuccess decreases to 7%. Their odds of succeeding rise to 13:1 (Table 3). Responding to the mediating impact of GPA, the decision rule using revision and total time for those students in GPA Q1 is presented in Table 4.

Table 4. Nonsuccess for Q1 GPA in Algebra 1 (74%)

	Q1	Q2	Q3	Q4
	If			
Number Revised		●	●	●
Total Time				●
	Then			
Nonsuccess= 39%	n=124			

If students in GPA Q1 can obtain a revision placement Q2 through Q4 and a total time of Q4 then their chance of nonsuccess drops from 74% to 39%, changing their odds of non-success from about 3:1 to a change of success of 1.5:1, better than even and comparable to the class as a whole. This is a dramatic improvement from almost certain failure. What this means is that even students with low GPAs can improve their chances of success if they revise a greater number of answers and spend a lot more time in the adaptive courseware.

Table 5 presents similar results for students in GPA Q2-Q3.

Table 5. Nonsuccess for Q2, Q3 GPA in College Algebra (39%)

	Q1	Q2	Q3	Q4
	If			
Number Revised		●	●	●
Total Time				●
	Then			
Nonsuccess= 24%	n=248			

Remembering that the Bonferroni procedure showed these two quartile GPA success rates to be non-significantly different from one other, they were treated as a combined group. Their non-success rate was 39%, roughly equivalent to the overall value for the class (41%). However, the rule indicated that if students in this group achieved Q2 through Q4 for revision and Q4 for total time, that their non-success rate decreased from 39% to 24%. Originally, their chance of success was 1.5:1. However, under the rule those odds rise to 4:1.

The final rule is presented in Table 6 and shows the change in odds for students in GPA Q4.

Table 6. Nonsuccess for Q4 GPA in Algebra (12%)

	Q1	Q2	Q3	Q4
If				
Number Revised		●	●	●
Total Time				●
Then				
Nonsuccess= 4%	n=123			

From the screening we learned that there was an independent 12% chance of non-success for these students. However, this rules states that if they obtain Q2 through Q4 for revision and Q4 for total time, then the non-success percentage drops to 4%. The odds of success go from 7:1 to 24:1, virtual certainty.

Table 7 presents the rule-based percentage lift in success chances for each of the GPA quartile groups.

Table 7. Rule-Based Success Gains by GPA Quartiles Based on Number Revised and Total Time Quartiles

GPA Quartile	Q1	Q2-Q3	Q4
Gains	35%	15%	8%

There is a 35% lift for students in GPA Q1, substantially increasing their chance of success. There is a moderate but helpful lift (15%) for students in Q2-Q3 and very little lift for those individuals in Q4 (8%). The rules were most effective for those who needed assistance the most, but, relatively ineffective for those who needed it least.

How College Algebra Became Adaptive At CTU

In 2012, Colorado Technical University (CTU) began researching adaptive learning as a tool to improve the academic experience for students and faculty in an open enrollment institution. CTU students are predominantly adults with an average age in their mid-thirties. As a result, they have varying degrees of work experience and training knowledge in subject areas. These varying levels of prior knowledge provide a unique challenge for instructors because these instructors teach students with diverse skill sets who may not have been in college for long periods of time. Adaptive learning provided a method to determine the knowledge level of students in a course so that content could be personalized. Dashboards included in adaptive learning tools also provided instructors visual insight into progress of students taking a particular course.

CTU programs are taught in an accelerated model; courses are 5.5 weeks in length and a full-time course load is considered 2 courses every 5.5 weeks or 4 courses in an 11-week quarter. Students are able to study part-time as an option to accommodate other obligations including employment, family obligations, and military commitment. When reviewing adaptive learning vendors, CTU set as priority the ability to implement adaptive learning in a number of courses. Realizeit provided faculty members the ability to create learning maps specific to course objectives as opposed to being provided maps for a particular subject, featured in several adaptive courseware platforms. Faculty at CTU created course content with the assistance of a curriculum design team led by a Vice President of Technology, who was actively engaged in the initial search for a vendor and engaged in the development of courses in collaboration with the Provost and Dean of General Education. Math and English faculty indicated a desire to participate in a pilot with Realizeit and MAT 102 (College Math) and ENG 104 (English Composition) were chosen as test bed courses for an initial implementation that included two course sections.

As noted previously, CTU is an open enrollment institution and students are required to take up to three math courses depending upon their program of study. MAT 102 is a basic math course with wide participation, often taken as a precursor to college Algebra. In 2012, college math faculty opted to pilot a fully online, fully adaptive college math course. The Realizeit adaptive platform provided CTU math faculty with the opportunity to develop content in the course based upon predetermined objectives. Faculty worked with curriculum designers to create adaptive learning maps including hundreds of questions and problems for students to review and complete during the course.

The processes of developing the learning maps was similar to those described by UCF; specifically, course objectives were broken down into granular concepts. A difference in the course development protocols at CTU was the inclusion of five top math faculty in the process to ensure that the perspectives of multiple faculty members were included in the course development. What made course development at CTU substantially different was the fact that courses were to be conducted totally online and at an accelerated pace when contrasted with the blended format and semester timeframe at UCF. CTU students addressed their knowledge of concepts and content determined appropriate to their level of achievement in the assessment index (determine knowledge) components of the course. Initially, remedial content was not included in the learning maps; however, tutoring was available to students through an online math tutoring provider.

Results from the pilot studies provided improvements in DFW rates in both the MAT 102 and ENG 104 courses over several course sessions and the Provost worked with colleges and programs to expand the use of adaptive learning into the general education program. CTU made a commitment provide faculty with the ability to work with CTU's curriculum design team to create content that was specific to course outcomes. At CTU, faculty created a master class that has been provided to all students, resulting in hundreds of participants taking the same course in a 5.5-week time period. The engagement of the Provost and Vice President of Technology in adaptive learning strategies was largely attributable to the perception that, overall, adaptive technology could have a substantial positive impact on students and faculty once the technology was implemented at scale.

CTU – A Time-Critical Setting

The UCF data suggested an approach to predictive modeling that provides learners with concrete and learnable actions that impact their odds of success positively. While a UCF course typically lasts 16 weeks, a CTU course lasts just 5.5 weeks. The short length of the terms at CTU produces a much more challenging environment for any predictive model. In this section of the study, we explore the impact of this time constraint on the effectiveness of predictive models.

Modeling

With the CTU data, we built a sequence of models that provided close to a real-time prediction of a student's changing chances of success in a course. This was enabled by building a framework that utilizes accumulated learning data at regular time slices throughout the course. Traditional approaches that build models based on the data at the end of the course are effective for setting expectations of the effort levels needed to give students the best chance of success, but are not particularly useful for setting incremental metrics or providing guidance based on a student's current progress. A sequence of models can overcome this shortcoming by providing a regular update on the student's real-time chances of success.

For this analysis, data were gathered from over 5,000 students across seven terms in a math course at CTU. The C5.0 algorithm, an improved version of C4.5 (Quinlan, 1993), was used to build models using some of the same Realizeit variables as those used the UCF study, augmented by additional indicators. The models attempted to predict the binary outcome of course success, defined as reaching the required grade set by the institution. CTU bases the final math course grade predominately on the final Calculated Score metric provided by Realizeit at the end of the term.

Table 8 explains the variables used in this analysis. Note that the models use only behavioral and attainment-based metrics that can be gathered by the platform because demographic-based data are generally not available.

Table 8. Variables Used in the CTU Models

Variable	Explanation
Total Time (totalTime)	The total time spent on learning
Number of activities (numActivities)	The total number of activities started
Nodes Attempted (numNodes)	The number of nodes attempted
Node Completed (numComp)	The number of nodes completed
Mean Knowledge Covered (meanKC)	The average KC across all objectives started
Start Day (startDay)	The number of days into the term on which the student started learning
Objectives Attempted (numObjectives)	The number of objectives attempted
Objectives Completed (numObjComp)	The number of objectives completed

The analysis addressed two specific questions:

1. At what point in the course is enough data available to make informed and accurate predictions?
2. How do the models change from one time slice to the next?

ENOUGH DATA

Adaptive platforms gather data on users as they interact with platform services. Realizeit collects highly granular logs of all student interactions with the platform and content. As the data grow, the platform builds a picture of how the student learns and uses that information to personalize and customize the learning experience.

Some interactions and usage types will be more informative than others, and some students will generate more data than others. For example, one student may answer practice questions, while another may engage in passive reading. The platform will gather information on each at differing rates and will, therefore, learn to make more effective recommendations and predictions for one student much sooner than another. This also will be true for the time slice-based predictive models, leading to the question of how much data is needed when building an accurate model that can surpass baseline models.

This analysis used the C5.0 algorithm to build a predictive model for each week of the CTU math course. Data generated by the students from the beginning of the course up to and including the split point such as mid-course were available for each model. The accuracy of all models, including both the C5.0 and simple majority class model, was measured using data from the following term.

The majority class model takes the most common outcome from the previous terms and uses it as the predicted outcome for all students in the subsequent term. If a course has very high or very low success rates, then this baseline model can be accurate. However, it may not be a particularly informative model because it does not provide insights into why students are successful or not.

Figure 3 demonstrates the predictive improvement of the decision tree over the baseline.

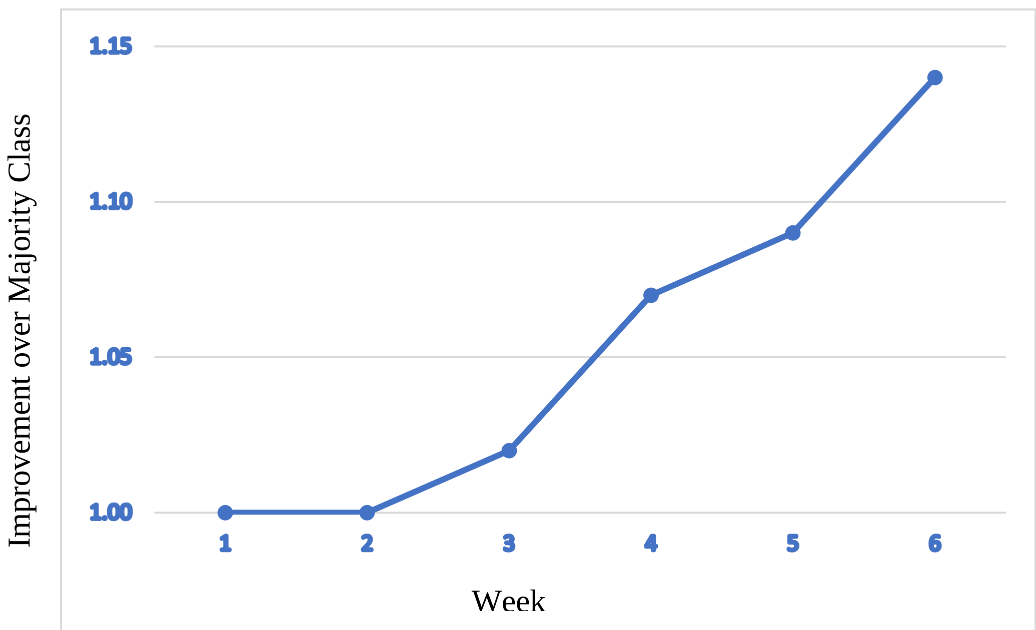


Figure 3. The Improvement Made by the Decision Tree Model over the Baseline Majority Class Model

The ratio of the accuracy of the two models provides a single measure of the improvement of the decision tree model over the simple majority class model. Another way of viewing this is as the payoff for the increased effort of building a decision tree.

For the first two weeks, there was virtually no improvement or payoff. The decision tree model gains no advantage over the majority class approach. Not until week three are there enough data available to beat the baseline. This is the point at which the data have sufficient signal in order to distinguish features that separate those students who will go on to be successful from those who will not. At this point, the model becomes not just accurate but also increasingly informative.

Requiring three weeks of data poses a considerable challenge in the CTU context because it leaves just two and a half weeks before course completion to intervene with students predicted to be unsuccessful. This three-week requirement of data is also present in the UCF context, however, with 16-week courses there is usually sufficient time to intervene.

VARIABLE IMPORTANCE

As seen above, there is a critical threshold at Week 3, after which, on average, there is enough signal compared to noise to make possible a determination with a high level of accuracy the prediction of which students will go on to be successful in the course. Therefore, we can expect the models and variables on which these models rely to vary considerably with an increasingly stronger signal, as the course progresses.

Predictor Importance (Kuhn & Johnson, 2013) allows us to measure how important each variable is to each model. This metric provides a measure of how much signal is present in each of the variables in the model when predicting an outcome. This information is useful for identifying which variables should be monitored most closely by educators to ensure a student is on track for success.

Comparing the time slice-based models enabled the measurement of the change in the predictor importance over time. To simplify the analysis, importance ranking was used rather than raw importance scores. The variables were ranked from most to least important or by strongest to weakest signal, using the raw scores.

Examining the results, there are several noteworthy outcomes. First, several variables, such as the number of objectives completed (numObjComp), start day (startDay), and the number of active days (numActiveDays) remain unimportant across all models/time slices. Those last two are interesting as they could be viewed as seat-time measures but contain little or no signal for course success. Figure 4 summarizes the change in variable ranks.

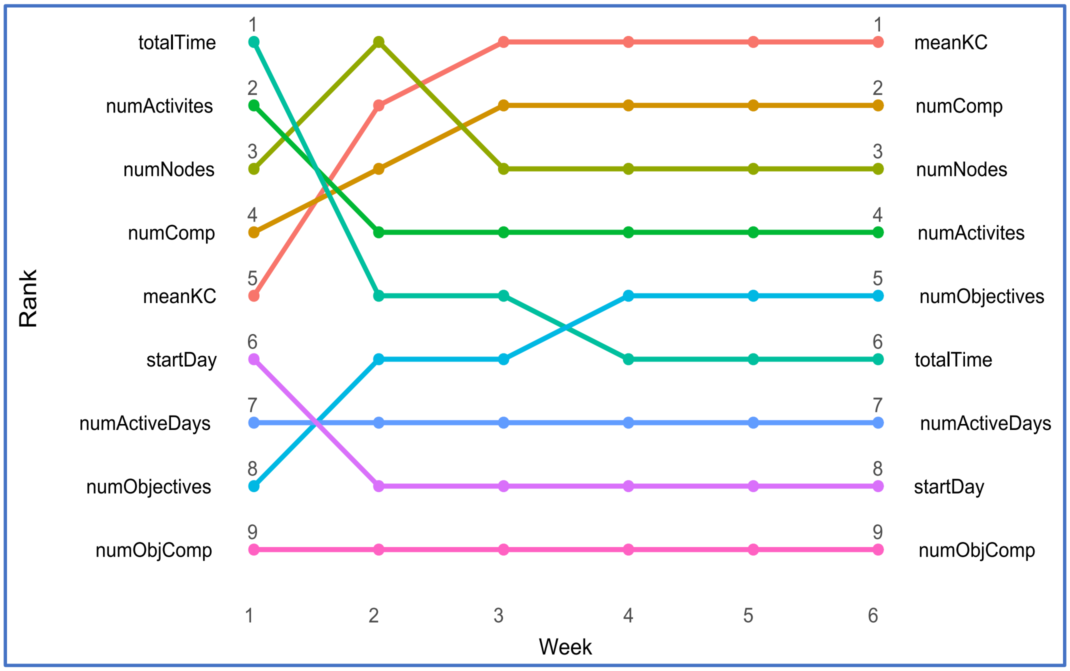


Figure 4. The Ranking of Variables for Importance over Time

Second, measures that capture the quantity of engagement, total time (totalTime), and the number of activities (numActivities) start as important but then decrease in rank over time, being replaced by the metrics that capture the quality of engagement. The number of nodes attempted (numNodes) captures the breadth of the engagement, the number of nodes complete (numComp), and the mean knowledge covered (meanKC) capture how much has been learned.

For educators, the variables that need to be monitored change as the course progresses. Metrics related to the traditional seat-time view were not predictive of student success. While at the beginning of the course, it is important to monitor effort levels, as the course progresses, it becomes more important to monitor the quality of the engagement and the level of progress of students.

CONCLUSION

The results of this study in two universities with considerably different infrastructures and student populations, conducted with their common platform provider, indicated that combining adaptive learning and learning analytics offers promise for helping students achieve successful outcomes in college Algebra. The adaptive framework advantage lies in its ability to personalize the educational experience, customize the content, and provide continuous assessment. Learning analytics in its most effective configuration finds outcome variables that identify the likelihood of student success early in a course. Ideally, those variables will lend themselves to training, instruction, or orientation. When combined, both approaches to education create a value-added model that benefits students; especially those who, without assistance, are likely to struggle and eventually fail.

Early work by Carroll (1963) paved the way for adaptive analytics, although at the time he proposed his model, learning analytics was yet to be developed or implemented. Consider the fundamental equation in which Carroll (1963) defined learning as the ratio of time spent and time needed.

$$Degree\ of\ Learning = f\left(\frac{Time\ Spent}{Time\ Needed}\right)$$ (Carroll, 1963, p. 6).

His expanded notion was:

$$f\left(\frac{\begin{matrix} Opportunity\ (Time\ Allowed) \\ Perseverance \\ Aptitude \end{matrix}}{Time\ Needed}\right)$$ (Carroll, 1963, p. 7).

The three terms in the numerator are key issues for predicting success and can be written in their Venn format as seen in Figure 5.

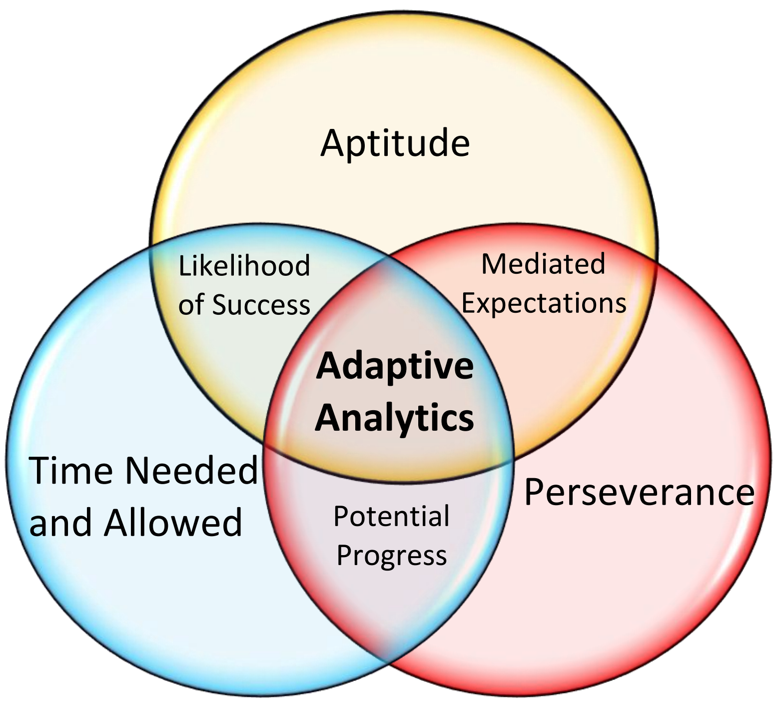


Figure 5. An Intersected Adaptive Analytics Model

The major components of the Carroll model, intersections of aptitude, perseverance, and time (needed and allowed) interact to form the meta-components. Mediated expectations shows that aptitude is not the only determinant because perseverance (engagement) can be an augmenting factor. Aptitude and time interact to provide a better indication of success likelihood. Perseverance and time combine as an indicator of potential progress. In his methods Carroll intimated the construct of learning analytics forming the proposition: If time allowed is constant then knowledge acquired will be the variable. However, if learning is the constant (approximately) then time allowed must be the variable. Put another way, if students spend exactly one 16- or 5.5-week semester in college Algebra then how much they learn, depending on their circumstances, varies. Students have different aptitudes, engage differently, and require different amounts of time to reach mastery.

The question becomes can we develop predictive methods and responsive models that compensate for the many different abilities and engagement idiosyncrasies students bring to their education? If so, what are the mediating student characteristics and behaviors, and is it possible to accommodate them in our instructional approaches? From these two questions, then, a third question emerges: Can an effective system of adaptive analytics be developed with responsive and actionable variables that can function in different contexts such as the University of Central Florida and Colorado Technical University? Further, what role can an adaptive learning platform provide in the support required by universities? Finally, it becomes incumbent on us to identify the level of granularity for which our methods will be most effective. Can we develop learning analytics that are effective for individual students or must we find like-cohorts and make some estimate of the odds of improvement in a general way, attempting to identify the most homogeneous groups possible? This frames the problem of individual versus prototype groups.

The UCF component of this study indicated that the suite of Realizeit indices contain two variables that account for most of the variance in student success: number of question or items revised and time spent engaged in the course. However, in the presence of entering grade point average their effectiveness diminishes. Because of this, UCF chose to use GPA not as a predictor but as a mediator by forming quartile cohorts. In order to be consistent, that declassification scheme was used on revision and time as well. The results from UCF indicate that such a declassification scheme compromises some individual precision but increases effectiveness of finding indicators that can be integrated into instructional protocols, thereby increasing the chances of student success. The best indicator of that outcome is that the UCF model gives students with virtually no chance of succeeding in college Algebra better than even odds. Certainly, there is variability for individuals regarding their chances, but as a whole, to some degree, UCF is able to ameliorate the academic Mathew effect that comes from being in the top GPA quartile. When GPA is used as a surrogate "treatment effect" it greatly reduces the uncertainty about helping students succeed. Time and revision have fellow travelers that can be effective as well. For instance, revision and practice are highly related and for the most part would accomplish the same outcomes. Revision just happened to emerge as the prime variable in the CRT analysis. There are any number of surrogates for time as well, such as a number of activities, nodes attempted and completed, and objectives attempted and completed, all of which are highly correlated with each other and with time. No variable in this system is unique and one variable effectively can be replaced by another with minimal loss of information. However, the encouraging part is that both revision and time lend themselves to instruction during the course, and can be monitored and incrementally improved. Finally, for the UCF study one should remember that this model was post hoc with index measures harvested at the conclusion of the course. However, the greatest lift for success was achieved for the group that needed it the most. In a more compressed time frame those opportunities diminish considerably.

In fact, the CTU study confronted the problem of time compression full on by, capitalizing on cumulative effect information. As emphasized in this work, end-of-course models (UCF) are excellent for determining prerequisites but are ineffective for continuous student status updates. This corresponds to the fundamental difference between summative and formative evaluation. The CTU work used a different variable configuration from UCF that was amenable to continuous time lag modeling. Given that the CTU course is 5.5 weeks in duration, it might be speculated that some of the indices do little to reduce uncertainty about student success. Secondly, given the compressed nature of the course, it might be further hypothesized that initially informative measures may not sustain their validity as the course progresses. In the CTU study, cross comparing the predictive accuracy of term end outcomes with the dynamic cumulative model indicates a relative informational standoff between the two for the first two weeks of class. In contrasting baseline and cumulative approaches, the information gain doesn't emerge until about 36% of the course is completed. After that point the information gain is accelerated and steep but there are most certainly exaggerated time pressures for helping students who have encountered difficulties so late in the course.

The second component of the CTU work identified a possibly more challenging aspect of comparing static (UCF) versus dynamic (CTU) predictive analytic models. The information they provide over time changes. So what predicted well at the beginning of the course diminished its importance over time, suggesting that, like the fundamental principles of adaptive learning, an effective adaptive analytics model will require continuous feedback. Although this phenomenon was identified in a 5.5-week course, there is every reason to believe that this will happen in a 16-week semester as well. However, both the UCF and

CTU models point to the fact that some form of time management and engagement through such things as revision activity are fundamental to effective prediction of success in college Algebra, independent of institutional context.

Metaphorically, this study used the “digital learning dust” that the Realizeit platform provides as a matter of course. These data, although assessment based, can be integrated into the instructional paradigm, not only providing predictive power, but also providing opportunities for students to overcome the challenges they encounter. In addition, by choosing the title “Adaptive Analytics: It’s About Time” we make a double entendre that first, emphasizes the importance of proper time use in the learning process. Carroll (1963) and others (Adam 2008; Norberg, Dziuban & Moskal, 2011) have demonstrated how time can be a major contributor to variations in human behavior, including learning. Therefore, the bottom line of this work is that, when mediated by prior achievement, genuine course engagement, combined with time needed, form the fundamental components for learning. The encouraging aspects of these two studies are that those elements identified are treatable student characteristics that can respond to instruction and intervention making a case for giving this approach serious future consideration, now that the concept of adaptive analytics viable, and provides the real possibility of actionable and continuing real-time information. Truly it’s about time.

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