Current Issues in Emerging eLearning

Volume 4 | Issue 1 Article 3

2017

Adaptive Learning: A Tale of Two Contexts

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INTRODUCTION

The higher education community is finding that adaptive learning systems have potential for accommodating student differences in an increasingly diverse population. Adaptive learning systems address this demographic variability by customizing course content according to differences in student skill sets (Brusilovsky & Millán, 2007).

In an adaptive learning environment students can navigate traditional length semester or quarter courses at an accelerated or extended pace. In most instances, students have repeat, rewind and replay options to help them achieve content mastery. What many educators are learning is that this added flexibility is an important component of student success. Certainly, there are some questions about the efficacy of adaptive instruction with respect to insight learning and disciplines in which skill sets are not the primary drivers and do not lend themselves to objective assessment. For instance, how does one design an adaptive system that capitalizes on social learning? In spite of questions raised regarding the range of learning situations for which adaptive systems are suited, this new modality has demonstrated the capability to “understand” where students are and to take those students where they need to be while making assessment part of the learning process.

ADAPTIVE LEARNING IN CONTEMPORARY HIGHER EDUCATION

There is a growing body of research on the outcomes that result from adaptive learning. Investigators have turned their attention to the cognitive, affective and behavioral aspects of learning as well as the impact of these systems on faculty members and the teaching environment. Although this body of investigation is in its early stages, considerable progress has been made.

For instance Nakic, Granic & Glavinic (2015) have argued that adaptive learning can improve student retention, achieve higher course outcomes, and provide a more precise measure of learning. Learning analytics reflect metaphoric progress indicators from students, helping faculty to determine the specific mastery needs for a topic, while at the same time allowing the opportunity to incorporate areas of demonstrated competency (Learning Gets Personal, 2016). Chang and others (2015) have addressed adaptive learning by using cognitive structure as a mechanism for pedagogical design. They built learning sequence tables and investigated their relationship to pattern navigation and simultaneous task performance. Walkinton (2013) has incorporated model tracing approaches to equation problem solving, finding that students who experienced learning personalization were able to compose different algebraic expressions more effectively.

Murray and Perez (2015) argued that educators have long known that learning is improved when instruction is personalized and adapted to individual student learning styles. According to these researchers, adaptive learning systems provide students the opportunity to assess their knowledge of a subject and receive appropriate content in real time. Assessment continues to occur as students learn, thus providing a technology that adapts to a student's specific needs. The integration of personalized learning offers both students and faculty the unique ability to enhance student success by identifying problem areas and addressing them immediately (Learning Gets Personal, 2016). Alli, Rajan, and Ratliff (2016) report that when at-risk students take partially adaptive blended courses, these students master content in half the time they require to learn the same content through traditional modalities. Moreover, their course pass rates increase by 33%. Smith (2013) found that adaptive artificial intelligence resulted in a dramatic increase in student success rates (success improved from 51% to 78%). Alsharmmari, Anane and Hedley (2015) concluded that adaptive learning approaches grounded in prior student knowledge resulted in higher student perceived learning gains when compared to non-adaptive approaches. Another study of cognitive and learning styles (active, reflective, sensing, intuitive, visual, textual, sequential and global) resulted in reduced cognitive load and a perceived increase in learning gains (Yang et al, 2013).

When using adaptive learning systems, students can be provided the opportunity to personalize their classroom content. Personalization of content increases students' competence and moves them towards achieving their full potential. Knowles (1980) argued that this is a key motivator for adult learners. Zembylas (2008) found that positive motivating emotions felt by online students aid their achievement, enthusiasm and excitement for the flexibility of online programs and increase their pride in their accomplishments. Alternatively, negative emotions found likely to hinder motivation and persistence include fear and anxiety of the unknown, alienation, stress and the guilt students may feel over an inability to balance multiple aspects of their lives effectively. For adult students, the challenge to achieve balance comes from the management of employment, family obligations and completing coursework. Mettler, Massey and Kellman (2011) found that, when compared to other learning modalities, adaptive sequencing based on response time and accuracy produced improved student success rates. Van Seters, Ossevoort, Tramper and Goedhart (2012) confirmed that students do avail themselves of individual learning paths. In addition, they concluded that students required varied numbers of exercises in order to demonstrate competency. An engaging feature of adaptive learning is that it allows a student to interact actively with course content while enabling the faculty member to respond to a student as the learning is occurring. In Wang, Wang, and Huang's (2008) study, adaptive strategies that allow students the opportunity for self-directed learning were shown to lead to student success. Fischman (2011) found a 99% completion rate among students taking a formal logic course via adaptive learning versus a 41% completion rate among students who took the class traditionally.

Practitioners must consider the effectiveness of adaptive learning in actual practice, as is the case with any educational technology tool used in the classroom. Research about adaptive learning tends to focus on the degree to which students succeed in mastering targeted learning objectives or outcomes, and the published results are mixed. Despotovic-Zrakic et al. (2012) found that students taking an adaptive learning version of a course did only moderately better on a business examination than did students who completed a non-adaptive version of the same course. Griff and Matter (2013) were unable to detect any appreciable differences in student achievement connected with their use of adaptive protocols. Murray and Perez (2105) concluded that adaptive learning has a negligible impact on student learning outcomes when outcomes are viewed as a component of learning quality. The researchers did conclude, however, that adaptive learning has a positive impact on other outcomes such as student persistence and engagement.

In order to be successful in an adaptive learning system, students must be taught how to self-mediate their learning as well as how to navigate course technology and learning management systems. Studies have shown that students have more success in school when they master self-regulatory processes that are oriented to achieving learning goals (Zimmerman, 2002). Students must do more than simply react to a set of instructions. Effective student and faculty training are integral to the successful implementation of adaptive technology in the classroom.

Forsyth, Kimble, Birch, Deel & Brauer (2016) present a protocol for effective adaptive learning:

1. Preparing students for the modality
2. Training and incorporating student practice with the technology
3. Motivating students
4. Considering learning style efficacy
5. Integrating automated grading
6. Considering amount and quality of feedback

Howlin and Lynch (2014) developed a framework for the delivery of personal adaptive content that corresponds to the adaptive principles outlined in the protocol proposed by Forsyth et al. The model proposed by Howlin and Lynch is based on: curriculum, pre-conditions, content, the adaptive intelligence engine, content filters, content selection, learning bits, questions and resources. In a sense, these researchers provided the gestalt for adaptive learning.

TWO CONTEXTS FOR ADAPTIVE LEARNING

THE UNIVERSITY OF CENTRAL FLORIDA

Founded in 1963, the University of Central Florida (UCF) in Orlando has the largest enrollment of any Florida university. Of the 63,002 students enrolled at UCF in fall 2015, 54,513 were undergraduates, with 6,618 being freshmen and 7,981 being transfer students. Seventy-six percent of UCF's undergraduate students received financial aid. Forty-three percent of students are minorities, with 23% being Hispanic. The average age of a UCF student is 24, with 23% of students being over the age of 25 (University of Central Florida, 2016).

UCF began as the Florida Technological University and technology has remained a strong focus of the university. UCF concentrates on providing quality instruction to the Orlando metropolitan area. The university has leveraged distributed learning as a strategic resource to promote access on an expanding scale in response to enrollments that have exceeded what can be accommodated in on-campus classroom space. During the 2014-2015 academic year, online learning courses accounted for 38% of total student credit hours and 3,718 course sections. In fact, UCF students are well experienced with online learning with 78% registering for at least one online course. UCF currently offers 18 online baccalaureate degree completion programs, 27 online master's degree programs and one doctoral program, in addition to online minors and certificates.

UCF students and faculty are well-versed in the use of technology in courses. Quality online instruction is maintained through a rigorous online faculty development program, as well as strong instructional design support.

The strategic use of technological resources in instruction is part of the institutional motivation for considering the use of adaptive learning in course instruction. In summer 2014 the university examined several adaptive learning platforms, with faculty and administrative input. Many systems offer off-the-shelf courses that provide easy start up, but allow for minimal or no instructional modifications and input from faculty. However, UCF faculty were interested in designing their own content; therefore, we focused our attention on content agnostic systems that maximized flexibility but also required significantly more up front workload to design and develop a course and course assessments. Companies were invited to demonstrate their systems and after careful consideration UCF chose Realizeit (Realizeit, 2016) as the adaptive learning system to pilot test.

Faculty members were recruited and college administrators were encouraged to consider the possibility of using adaptive learning as a means to address access, quality, and security in online courses. Initial costs to students were absorbed by pilot testing in online courses and utilizing UCF's distributed learning (DL) fee to pay for access to Realizeit.

Initially, individual faculty members from Psychology, Nursing, and Mathematics volunteered to redesign their courses utilizing adaptive learning. The Psychology faculty member teaches the course, General Psychology (an introductory course), as part of the general education program curriculum. The course enrolls a large number of undergraduate students each semester. Since Psychology offers an online program, at least one section of the General Psychology course is offered online each semester.

Another UCF faculty member teaching Pathophysiology as part of the Nursing requirements utilizes case studies in course instruction. Adaptive learning was appealing to her for its flexibility to create "adaptive" case studies in which each question allows for a range of values, thereby ensuring that each student receives a case study that is unique and realistic.

Finally, one UCF mathematics instructor regularly taught College Algebra online, a course that is notoriously challenging for many students. She was eager to use adaptive learning as a means to redesign this course and to scaffold instruction so that students who struggled would be directed to the exact content needed for remediation. Moreover, the adaptive system also accommodated students' preferred modes of instruction (video, audio, text). Currently, she is working on the mathematics sequence from College Algebra to Calculus, hoping to create a method to provide strong support for online students.

COLORADO TECHNICAL UNIVERSITY

Colorado Technical University (CTU) began operation in 1965 as the Colorado Electronic Training Center (CETC). In 1970, the institution received approval from the State of Colorado to offer degree programs and the name was changed to Colorado Electronic Technical College. In 1971, the first classes entered into associate's degree programs in Biomedical Engineering Technology and Electronics Engineering Technology and in 1972 these programs received accreditation from the Engineer's Council for Professional Development (ECPD – the forerunner of the Accreditation Board for Engineering and Technology, or ABET). By 1975, the institution was renamed Colorado Technical College (CTC) and the following year, CTC entered candidacy for regional accreditation with the North Central Association of Colleges and Schools (NCA) and it received initial accreditation in 1980. (NCA later became the Higher Learning Commission, or HLC).

CTU achieved several significant milestones in the 1990s:

- 1993: ABET accreditation of the BS in Electrical Engineering
- 1994: HLC approval to offer doctoral programs
- 1995: Name change to Colorado Technical University (CTU)

In the year 2000, CTU offered online programs for the first time. The University now offers over 50 core academic programs, from associate to doctorate, of which over 40% are delivered fully online. Currently, the student population is approximately 24,000.

Colorado Technical University's mission is to provide industry-relevant higher education to a diverse student population through innovative technology and experienced faculty, enabling the pursuit of personal and professional goals. Programs are offered in career-focused disciplines including engineering, computer science, health sciences, business and management, criminal justice, information technology and general studies. In addition, concentrations are offered within selected programs to provide students with options for specialization.

CTU serves a diverse population and the average age for online students is 36 with female students accounting for 60 percent of the population. CTU is an open enrollment institution and students enter CTU with varying levels of academic and professional experience in addition to transfer credit.

Because of the perceived advantages of personalized learning content, CTU began piloting courses with adaptive learning at CTU in the beginning of 2012. CTU implemented the Realizeit adaptive learning system branded as Intellipath and all materials related to adaptive learning at CTU as well as platform icons are consistently referred to as Intellipath. CTU's initial pilots in adaptive learning included pilots in math and English courses, offering three courses to approximately 100 students. Because of positive results, student and faculty feedback, CTU expanded the adaptive course as indicated in Table 1.

Table 1. Demographics for the Adaptive Learning Students at CTU

	Courses Launched	Total Offered	Unique Users*	Population Adoption*
2012	3	3	358	1.5%
2013	16	19	16,075	55%
2014	25	44	29,634	78%
2015	63	107	32,319	79%

* "Unique Users" indicates the number of individual Intellipath users per year.
** "Population Adoption" refers to the percentage of CTU's population using Intellipath each year. All data is as of December 14, 2015.

Courses are offered in a number of disciplines and include associate to doctoral level content. The initial rationale for adopting Intellipath (aka Realizeit) was to provide CTU faculty the opportunity to create learning maps and adaptive content that aligned to course objectives. CTU faculty members who develop adaptive learning courses are provided training and templates and work with an instructional design team to create course content.

CTU adhered to a disciplined model for the rollout and implementation of adaptive learning technology including the review of student and faculty feedback after the completion of each course in which the technology was used. Additionally, as courses were being implemented, we conducted focus groups with faculty and with students to discuss experiences and gather feedback about a range of topics including technology usability and the overall experience of learning within the adaptive technology, and perceptions regarding the ability of the technology to enhance course content. By analyzing the student and faculty experience at targeted intervals throughout program development and the initial 2012 pilot rollout, CTU was able to make critical adjustments before extending the platform to larger audiences.

At this time, the CTU program has grown to include approximately 120 courses utilizing adaptive technology.

THE ADAPTIVE LEARNING PLATFORM

Realizeit is an adaptive learning platform that integrates with the learning management system (LMS) to provide course content navigation to students. The system is content agnostic, allowing faculty to create and build courses within the system or to import content from either existing online course materials or open educational resources. Single sign-on authentication and course and group synchronization are supported, in addition to automatic grade transfer (including the transfer of metrics and comments) to the course gradebook.

Realizeit's adaptive engine incorporates intelligent logic using Bayesian estimation, adapting and evolving as learners progress through the system. The adaptive learning system suggests alterative pathways depending on students' attainment on assessment outcomes, prior knowledge and behavior, and rules specified by instructors. Realizeit supports adaptive assessment and can incorporate multiple learning media (text, video, audio, etc.) depending on how students learn best. The system guides students through individualized pathways to optimize their learning (Howlin & Lynch, 2014).

Students have the ability to choose an alternative path through the content, to attempt new content, or alternatively to review and to practice previous concepts. However, the system is structured to optimize learning and to verify learner mastery. Instructors can identify learning objectives for students. Analytics data provided by the system can improve the faculty member's interaction and intervention with students.

Conference conversations between the authors led to this cooperative study. Because both CTU and UCF implement a version of the Realizeit platform, a comparison of the two student cohorts' responses to this modality would enhance our understanding of adaptive learning across differing organizational and instructional contexts.

THE STUDY

The purpose of this study was to compare student reflections about their adaptive learning experiences using the same platform in two contextually different universities. Learners from the two different university contexts responded to a validated survey instrument. Subsequently, responses among members of the two groups were contrasted. The latent dimensions underlying the item responses were derived for each university dataset and compared for factor invariance. Because the factors between the institutions coincided, the student groups were combined in order to produce an overall solution. The common factor scores were computed and tested for significant differences between the two universities. Additionally, a two group cluster solution based on student willingness to reengage in adaptive learning was used to identify positive and somewhat more ambivalent students as gauged by their scores on the factors.

THE STUDENTS

Students enrolled in UCF's fully online, fully adaptive General Psychology course were surveyed in the fall 2014 and spring 2015 semesters with response rates of 93% (117/125 students) and 73% (127/175 students), respectively. The students in the CTU sample (n=1,440) represented a 10% response rate across one hundred courses in general education, business, informatio6n technology, and criminal justice. Demographics of those who responded are shown in Table 2 and discussed below.

THE INSTRUMENT

After a careful search of the literature regarding student reactions to adaptive learning, a survey was constructed with input from instructors and researchers. The final instrument (included as Appendix A) captured student reactions to:

- The adaptive learning system, including ease of use, helpfulness of feedback and direction, and students' perceived accuracy of the system's assessment of their learning,
- Adaptive learning as an instructional method, including students' likes and dislikes, its impact on their course progress, their interaction with course content, and time spent on material,
- Overall students' likes, dislikes, and suggestions for improvement for the course
- Overall student demographics including age, gender, ethnicity, academic standing, expected grade, employment, and current course load.

Subsequent to pilot-testing with students and faculty familiar with the adaptive learning system, the instrument was revised and finalized. The final protocol consisted of 27 items, created in Likert response format augmented with open-ended responses to allow students to provide more granular feedback. At UCF the instrument was coded as an Instructure Canvas graded survey and included in each adaptive learning course. The survey was announced to students near the end of each semester.

CTU administered the survey created by UCF, through an internal survey engine facilitated by CTU academics. Each student taking an adaptive learning course received a link to their survey via email and instructors also posted announcements requesting students to complete the survey. At CTU, student surveys were administered to students after the conclusion of each course.

METHODOLOGY

Student responses to the adaptive learning survey instrument across the two institutions were analyzed with contingency tables and Monte Carlo probabilities that provided some information about areas of agreement and dissimilarity. In addition, other properties of the survey instrument were assessed. Reliability was assessed using coefficient alpha (Cronbach, 1951) for both CTU and UCF student responses. The domain sampling properties of the instrument were also evaluated. In conducting comparative studies such as this there are two important sampling issues involved, one statistical and one psychometric. The statistical sampling issue concerns the degree to which the student samples included in the study represent the underlying populations of their respective institutions. The second and equally important issue concerns the domain representativeness (psychometric sampling) of the questionnaire items. That is, can the investigator demonstrate that the items included on the questionnaire are representative of the domain of interest, in this case student perceptions of adaptive learning? Note that this is a validity issue rather than one of reliability.

In order to address this characteristic, Kaiser and Rice (1974) developed a monotone evidence-based index from a theorem developed by Guttmann (1955) showing that, as domain sampling improves, the inverse of the item correlation matrix approaches a diagonal. The Measure of Sampling Adequacy (MSA) developed by Kaiser and Rice capitalizes on that property. The index is limited by 0 and 1 with values in the .80s and .90s indicating that the investigators can have confidence in their domain sample. As MSA values decrease to the .60s, further work is not advisable because most likely the analysis will be based on measurement noise. Fundamentally, the MSA answers the question: Do you have an adequate sample of items from your domain of interest? In addition to an overall MSA, the developers created an individual value that gives an indication for each question about how well each question belongs to the family, psychometrically-speaking. Of course such information can be informative and useful before proceeding with domain structuring. Dziuban and Shirkey (1974) developed a strategy for evaluating one's data prior to any factoring work. Their strategy was used in this study.

THE DIMENSIONALITY OF STUDENT RESPONSES WITHIN AND BETWEEN UCF AND CTU

The investigators sought to determine the number of underlying dimensions of student responses to their adaptive learning experiences that might be identified at each of the universities. In addition, they sought to assess the degree to which the components corresponded in the two distinct teaching and learning environments. Customarily this problem is approached by applying the factor analysis method in the classic factor invariance problem. For this study the survey instrument responses were 'factored' with Guttman's (1953) image analysis. The best way to understand this procedure is to imagine data composed of two separate pieces:

- the proportion of an individual variable that can be predicted from the remaining variables in the dataset (the image)
- the segment that is not predictable from the remaining variables (the anti-image)

Guttman developed the procedure as a response to the indeterminacy of most factor analytic procedures (Mulaik, 1972).

The number of image factors retained in the final solution was determined with a procedure proposed by Dziuban and Shirkey (1993) and further explored by Hill (2011). The process calls for an initial assessment of the student responses with the MSA followed by sequential MSA computation once the effect of each component has been removed, in turn, from the original system. At the point when a value in the .60s is obtained, the investigator has evidence that there are no more meaningful components to be found in the reduced dataset. The initial pattern matrices were transformed (rotated) according to the direct oblimin procedure (Carroll, 1953). Pattern coefficients absolutely larger than .30 were used for interpretation purposes.

Once the final dimensionality of the dataset was determined, factor scores for each subject in the sample were derived using the Anderson Rubin (1949) method. These scores have a mean of zero, a standard deviation of one, and a reasonably good relationship to the estimated factor validity. Those scores were rescaled to a mean of 50 and standard deviation of 10 for ease of interpretation. Subsequently, these scores were tested for significance across universities and on a two group K-means cluster, based on the question that indexed whether or not adaptive learning helped students in their knowledge progression. Hedges' g effect sizes (Hedges, 1981) were calculated for all factor score comparisons. Responses were received from 1,440 CTU and 240 UCF students.

RESULTS

Table 2 presents the comparison of student demographics for the two universities.

Table 2. Student Demographics for the Two Universities (UCF n=240, CTU n=1,440)

Age	UCF	CTU	p = .00
18-24	88	8	
25-34	9	27	
35-44	0	28	
45-54	1	26	
55-64	0	10	
65 or older	2	1	
Prefer not to answer	0	1	
Gender	UCF	CTU	p = .00
Male	42	27	
Female	57	72	
Prefer not to answer	1	1	
Academic Standing	UCF	CTU	p = .00
Freshmen	98	90	
Sophomore	0	8	
Junior	2	3	
Ethnicity	UCF	CTU	p = .00
American Indian/Alaska Native	0	2	
Asian	6	1	
Black	12	28	
Hispanic/Latino	17	5	
Multi-racial	3	4	
Native Hawaiian/Pacific Islander	0	1	
White	30	52	
Prefer not to answer	30	8	
Expected Grade	UCF	CTU	p = .00
A(-)	74	62	
B(-/+)	23	28	
C(-/+)	3	7	
D(-/+)	0	2	
F(-/+)	0	1	
Number of Fully Online Courses Taken	UCF	CTU	p = .00
1	22	13	
2	28	8	
3	15	9	
4 or more	35	71	
Employment Weekly Hours	UCF	CTU	p = .00
0	43	36	
1-9	8	3	
10-19	11	2	
20-29	20	7	
30-39	9	8	
40+	10	43	

Comparisons were made on age, gender, academic standing, ethnicity, expected grade, number of online courses taken and weekly employment. All comparisons yielded significant differences between the universities representing the student populations. CTU students were older than their UCF counterparts with over 80% of them being in the 25-54 age range while 88% of the UCF students were 18 to 24 years old. CTU student respondents were predominately female, 72%, compared to 57% at UCF. Both institution responses were dominated by freshman (UCF: 98%, CTU: 90%). The majority of CTU students were white (52%) compared to UCF's (31%). The black population at CTU was roughly twice that of UCF (28% compared to 12%) but the Hispanic/Latino population at UCF was larger than at CTU (17% compared to 5%). The vast majority of students at both universities expected a grade of B or better in their courses with no students expecting a D or F at UCF. The highest grade expectation came for UCF with 98% expecting a grade of A or B. A larger proportion of CTU students (71%) had taken four or more online courses and by far CTU had the largest proportion of students who worked 40 hours or more (43% compared to 10%).

Table 3 presents the comparison results of student responses to their adaptive learning experience at the two universities with regard to the ease or difficulty of the adaptive platform. The five-point Likert scale responses were declassified into three ordinal categories in order to reduce the ambiguity that arises from the responses to adjacent extreme Likert values. This process tends to clarify student responses in a categorical classification sense with the opportunity cost of reduced reliability. However, in this case the declassification resulted in a modest decrease (5%) in reliability, which is a small price for the added clarity.

Table 3. Student Response Percentage Comparisons for the Two Universities Regarding the Ease or Difficulty of the Adaptive Learning Experience (UCF n=240, CTU n=1440)

	Difficult	Ambivalent	Easy	P
Sequence of Items				
UCF	13	45	42	.00
CTU	25	50	25	
Learning Material				
UCF	16	46	38	.00
CTU	24	50	27	
Questions Asked				
UCF	28	47	25	.22
CTU	33	47	21	
The Learning Path				
UCF	7	26	67	.55
CTU	10	24	67	
The Guidance Panel				
UCF	3	36	61	.00
CTU	7	24	69	

Three of the items produced significant differences between the two universities. The UCF students saw the sequence of items (UCF: 42%; CTU: 25%) and learning material (UCF: 38%; CTU: 27%) as significantly easier than CTU students. The other significant finding in this category of items suggests that that the CTU students (CTU: 69%; UCF: 61%) found the guidance panel easier to use. This is a logical finding since mathematics relies on a logical sequence that requires more stringent documentation of progress. Table 4 presents responses of students regarding their perceptions of the quality of the adaptive learning experience.

Table 4. Student Response Percentage Comparisons for the Two Universities Regarding the Quality of the Adaptive Learning Experience (UCF n = 240, CTU n = 1440)

	Disagree	Ambivalent	Agree	P
AL helped me learn better than no AL				
UCF	6	16	78	.00
CTU	12	6	82	
AL gave me feedback on objectives				
UCF	6	18	77	.00
CTU	8	10	82	
The instructions in AL were clear				
UCF	4	9	87	.31
CTU	6	8	86	
The ability levels reported were accurate				
UCF	10	17	73	.08
CTU	7	14	79	
AL became personalized to me over time				
UCF	10	27	63	.00
CTU	8	14	78	
Grading accurately reflected knowledge				
UCF	9	16	75	.01
CTU	9	11	81	
AL's exercises measured learning				
UCF	5	21	73	.00
CTU	7	11	82	
AL increased my engagement				
UCF	8	18	75	.00
CTU	7	9	85	
AL was easy for me to use				
UCF	3	12	85	.20
CTU	5	10	86	
I would take another AL course				
UCF	9	13	78	.01
CTU	6	8	86	

Although there were some significant differences in the student responses across the institutions, a general observation of the table shows a strongly positive response by students at both institutions. All significant differences indicated that the CTU students were even more positive that the UCF students, however the differences reflect small variations in almost complete agreement. Only one of the UCF categories dropped below the 70% agreement level (adaptive learning became personalized to me over time: 63%). Alternatively, no CTU student agreement category dropped below 75%. This institutional trend is best reflected in the question that asked students whether or not they would take another adaptive learning course. Approximately 78% of the UCF students indicated that they would register for another course while 86% of the CTU students responded affirmatively. The fact that the difference was significantly different from zero is rendered moot by the near unanimously positive responses of both student groups. Table 5 presents noteworthy findings about student interaction, their progress, and the next steps for students to follow within the system as suggested by Realizeit.

Table 5. Student Response Percentage Comparisons for the Two Universities Regarding Interactions, Progress, and Next Steps in the Adaptive Learning Experience (UCF n = 240, CTU n = 1440)

	Less	The Same	More	P
How often did you interact w/ students?				
UCF	75	19	6	.00
CTU	39	53	8	
	Unhelpful	Ambivalent	Helpful	P
How helpful did you find the guidance panel				
UCF	2	28	71	.00
CTU	6	16	78	
	Never/Rarely	Sometimes	Often/Always	P
How often did you follow suggested next steps				
UCF	18	29	53	.00
CTU	5	16	79	

The difference between reported CTU and UCF students was noteworthy. Over 75% of the UCF students indicated less interaction compared to about 39% of the CTU students. With respect to the same amount of interaction, 53% of the CTU students responded affirmatively to the questions reading "How often did you interact with other students comparted to a class not using Realizeit?" while only 19% of the UCF students indicated a same amount of interaction when compared with a non-adaptive course. Very few students in both groups experienced more interaction (UCF: 6%; CTU: 8%).

We asked students "How helpful did you find the guidance panel?" This feature helps students track their progress through the module and also recommends next steps to take. Once again, both groups responded positively about this feature of adaptive learning with 70% or more in the affirmative. Clearly, in the view of both cohorts this progress monitoring constitutes a helpful feature of the platform.

Students in both groups were posed the survey question, "How often did you follow suggested next steps?" In responding to this survey question, members of each group provided key indications of the way they behaved in response to suggestions offered by the adaptive learning platform regarding the next steps that learner could/should take. There appears to have been an important and significant difference in the way members of one versus the other group behaved in response to this suggestion feature of the adaptive platform. In the UCF group, 18% of respondents indicated they *rarely or never* followed suggested next steps, whereas only 5% of the CTU students indicated that they *rarely or never* followed suggested next steps. Fifty-three percent (53%) of the UCF students indicated they *often or always* followed suggested next steps while 79% of the CTU students indicated they *often or always* followed suggested next steps. Apparently, the two student groups took considerably different approaches toward adaptive learning.

COMPARISON OF THE UCF-CTU FACTOR INVARIANCE

Table 6 presents the derived pattern matrix for the UCF student responses to their adaptive learning experiences. Three factors were retained based on the Dziuban-Shirkey criterion with an overall MSA of .86 for the variable set, placing its value in the excellent domain sampling range. After removing the three factors, the residual MSA for the system was .50, indicating that any remaining variability was primarily caused by noise. The alpha reliability coefficient for the responses was .89 with an average correlation among the factors of .22.

Table 6. Transformed (Direct Oblimin) Pattern Matrix for the UCF Student Survey Responses (n = 240)

Item	Factor 1	Factor 2	Factor 3	MSA
Overall, AL helped me learn better than not having AL	**.74**	-.22	.00	.94
Given a choice, I would take another course using AL	**.74**	-.09	-.06	.93
AL gave me feedback to stay on track with course objectives	**.74**	-.05	-.01	.91
The ability levels reported by AL were accurate	**-.72**	.02	.05	.94
AL increased my engagement with the course content	**.71**	-.11	-.09	.84
AL's exercises were effective in measuring my learning	**.70**	.19	.08	.91
The instructions in AL were clear	**.70**	.03	.05	.89
The AL system became personalized to me over time	**.67**	.12	.07	.87
The grading accurately reflected my knowledge	**.61**	.10	.03	.97
AL was easy for me to use	**.54**	-.05	**.31**	.95
How helpful did you find the guidance panel supplied by AL?	**.31**	.03	-.27	.97
Rate the difficulty of the learning material used to teach this course	-.02	**.78**	-.02	.79
Rate the difficulty of the sequence of items on the learning path	-.02	**.75**	-.12	.87
Rate the difficulty of the questions asked during this course	-.08	**.72**	.02	.80
How often did you follow the suggested next steps in AL?	.27	**.35**	.03	.97
How easy was the guidance panel to use?	.05	.15	**.81**	.74
How easy was the learning path to use?	.00	.19	**.76**	.75
How often did you interact with other students vs. no AL	.04	.11	**.38**	.95
Eigenvalues	5.3	1.9	1.4	
Overall MSA = .86				
Residual MSA = .50				
Average factor correlation = .22				
Alpha = .89				

Factors:
1 = learning environment
2 = guidance path
3 = progression

Results of the identical procedures applied to the CTU data are presented in Table 7 with corresponding results. The overall MSA of the dataset was .90 with a residual value of .58 after three factors had been extracted. The alpha reliability coefficient for the dataset was .89 with an average factor correlation of .24.

Table 7. Transformed (Direct Oblimin) Pattern Matrix for the CTU Student Survey Responses (n = 1440)

Item	Factor			
	1	2	3	MSA
AL's exercises were effective in measuring my learning	**.91**	-.01	-.04	.94
The grading accurately reflected my knowledge	**.90**	.00	-.10	.94
AL increased my engagement with the course content	**.88**	.00	-.03	.95
The ability levels reported by AL were accurate	**.85**	.03	-.03	.94
The AL system became personalized to me over time	**.84**	.03	-.03	.97
Given a choice, I would take another course using AL	**.79**	.00	.06	.94
AL was easy for me to use	**.68**	.03	.15	.95
AL gave me feedback to stay on track with course objectives	**.62**	-.02	.15	.92
The instructions in AL were clear	**.54**	-.03	.20	.89
Overall, AL helped me learn better than not having AL	**.47**	.09	.08	.95
How often did you follow the suggested next steps in AL?	**.30**	-.03	.04	.98
How often did you interact with other students vs. no AL?	**.31**	.03	-.09	.95
Rate the difficulty of the learning material used to teach this course	.24	**.88**	-.01	.79
Rate the difficulty of the questions asked during this course	-.01	**.87**	-.01	.80
Rate the difficulty of the sequence of items on the learning path	.02	**.81**	.10	.87
How easy was the guidance panel to use?	-.02	.11	**.91**	.74
How easy was the learning path to use?	-.01	.13	**.90**	.78
How helpful did you find the guidance panel supplied by AL?	.22	-.05	**.39**	.97
Eigenvalues	7.1	2.1	1.3	
Overall MSA = .90				
Residual MSA = .58				
Average factor correlation = .24				
Alpha = .89				

Factors:
1 = learning environment
2 = guidance path
3 = progression

Table 8 clarifies the data on pattern similarities between the universities.

Table 8. Similarity Coefficients and Salience Correspondence for UCF and CTU Pattern Matrices

Component	r	ϕ*	Salience Correspondence
Learning Environment	.85	.89	94%
Guidance Path	.92	.84	93%
Progression	.70	.72	88%

* Phi coefficient

Rather than interpret the UCF and CTU patterns separately we interpret the data integrally; the factor similarity coefficients presented in Table 8 explain our reasoning. The correlations among the factors across institutions were high and positive ranging from .70 to .92. When the variables in the patterns were assigned a 0 or 1 according to whether or not they achieved the .30 salience criterion, the resulting phi coefficients were high and positive as well, ranging from .72 to .89. When the percentage of salient variables for corresponding factors were computed those values ranged for 88% to 94%. This presents compelling evidence that although the contexts and student demographics of the University of Central Florida and Colorado Technical University are considerably different, the underlying dimensionality by which students in the respective institutions respond to their adaptive learning experience is for all intents and purposes identical.

WHAT DO THE FACTORS MEAN?

Given these findings, we combined the instructional datasets and analyzed them with identical procedures. The result of that analysis is resented in Table 9. A factor pattern similar to the individual UCF-CTU analyses may be observed. Three factors were extracted with an overall MSA of .91 reducing to a residual value of .60. The alpha reliability coefficient was .93 with an average correlation among the factors of .24. In sum, the combined group analysis was virtually identical to the individual institution results.

Table 9. Transformed (Direct Oblimin) Pattern Matrix for Student Survey Responses – Combined Samples (n = 1680)

Item	Factors 1	2	3	MSA
AL's exercises were effective in measuring my learning	**.88**	.04	-.04	.96
The grading accurately reflected my knowledge	**.86**	.05	-.10	.94
AL increased my engagement with the course content	**.85**	.01	-.02	.95
The ability levels reported by AL were accurate	**.83**	.06	-.03	.91
The AL system became personalized to me over time	**.82**	.02	.00	.91
Given a choice, I would take another course using AL	**.78**	.01	.06	.93
AL was easy for me to use	**.65**	.06	.17	.94
AL gave me feedback to stay on track with course objectives	**.63**	.00	.13	.84
The instructions in AL were clear	**.55**	.01	.15	.91
Overall, AL helped me learn better than not having AL	**.50**	.06	.07	.94
How often did you follow the suggested next steps in AL?	**.32**	-.04	.05	.93
How often did you interact with other students vs. no AL?	.26	-.02	-.09	.94
Rate the difficulty of the learning material used to teach this course	.03	**.88**	-.03	.78
Rate the difficulty of the questions asked during this course	.01	**.87**	-.04	.85
Rate the difficulty of the sequence of items on the learning path	.01	**.81**	.08	.80
How easy was the guidance panel to use?	-.01	.07	**.91**	.80
How easy was the learning path to use?	-.01	.09	**.90**	.80
How helpful did you find the guidance panel supplied by AL?	.23	-.06	**.38**	.96
Eigenvalues	6.8	2.1	1.3	
Overall MSA = .91				
Residual MSA = .60				
Average factor correlation = .24				
Alpha = .93				

Factors:
1 = learning environment
2 = guidance path
3 = progression

The first factor, *learning environment*, was the dominant factor, and was comprised of eleven variables that reflected a wide range of student reactions to adaptive learning. Those markers included: assessment and the assigning of grades, engagement, accurate ability levels, effective personalization, ease of use, effective support, and a willingness to re-engage in adaptive learning. This factor reflected the well understood proposition that students evaluate their learning environment with a preconceived notion of an effective learning situation (Wang, Dziuban, Cook, & Moskal, 2009). In many respects this corresponds to the construct of a psychological contract – a situation wherein the instructor and students expect different things from the class and each other but never articulate them (Dziuban, Moskal, Thompson, Kramer, DeCantis, & Hermsdorfer, 2015). The second factor common to both institutions was composed of the course learning material, the questions asked, and the sequencing of items, all of which indicate that students in the adaptive environment react to the *guidance path* provided to them. The third factor produced salient pattern coefficients regarding the guidance panel and its effectiveness and regarding the learning path developed by the system. This factor signifies student concern with accurately indexing their *progression* through the course material. The underlying dimensions by which students respond to their adaptive learning experience can be summarized by their decisions regarding whether or not adaptive learning provided an effective learning environment, whether or not the system provided effective guidance, and whether or not it facilitated a sense of progression.

Figure 1 and Table 10 below provide the results of the comparison of the scores on the three common factors (*Learning Environment*, *Guidance Path* and *Progression*) for the two institutions.

Figure 1. Factor score comparisons for the two institutions

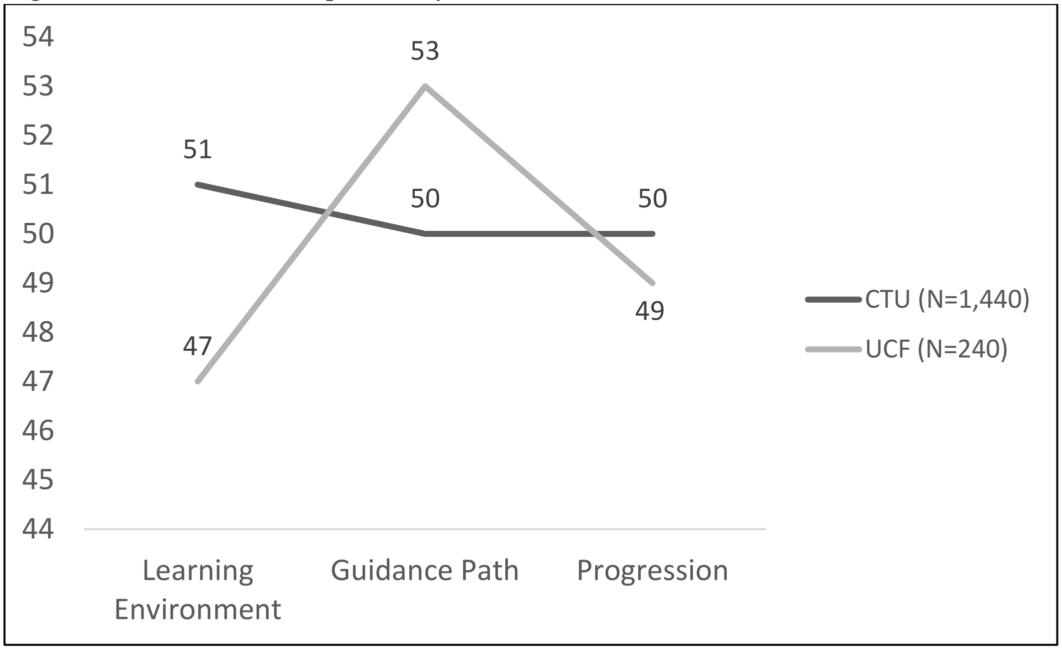

Table 10. Significant Differences and Effect Sizes for the Factor Score Between the Two Universities (UCF n = 240, CTU n = 1440)

		n	$\bar{x}$	SD	p	ES
Learning Environment	UCF	240	47	7.9	.00	.39
	CTU	1440	51	10.2		
Guidance Path	UCF	240	53	9.0	.00	.34
	CTU	1440	50	10.1		
Progression	UCF	240	49	7.6	.29	.07
	CTU	1440	50	10.3		

Remembering that the factor scores were rescaled to a mean of 50 and standard deviation of 10, two of the factors showed significant differences. The CTU groups were more positive on the average regarding the adaptive learning environment than the UCF group (CTU: 51%; UCF: 47%) with a moderate effect size of .39. However, the UCF group was more positive about the effectiveness of the guidance path than the CTU students (UCF: 53%; CTU: 50%) with, once again, a moderate effect size of .34. The progression factor scores yielded virtually identical results for the two universities (UCF: 49%: CTU: 50%, p = .29).

When the students were clustered by whether they perceived that adaptive learning helped them learn, two groups emerged that crossed institutional lines. That result is presented in Figure 2 and details are provided in Table 11.

Figure 2. Factor score comparisons for the two clusters

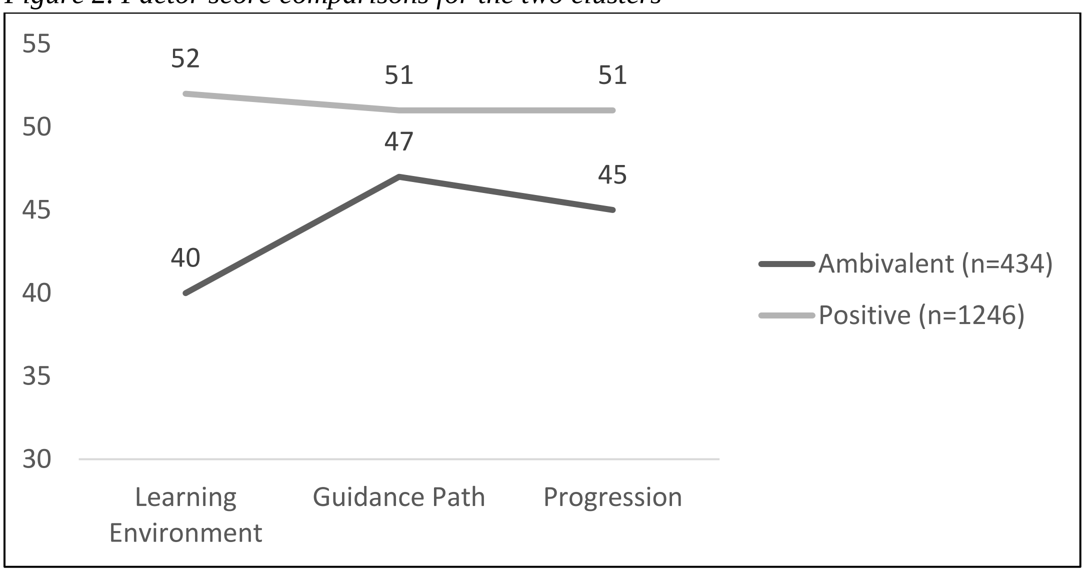

Table 11. Significant Differences on Effect Sizes for the Factor Scores Between the Two Clusters

		n	$\bar{x}$	SD	p	ES
Learning Environment	Ambivalent	434	40	12.5	.00	1.5
	Positive	1246	52	7.6		
Guidance Path	Ambivalent	434	47	11.6	.00	.48
	Positive	1246	51	9.5		
Progression	Ambivalent	434	45	11.6	.00	.74
	Positive	1246	51	9.2		

One group was clearly more positive while the other was somewhat more ambivalent about adaptive learning. The most noteworthy finding is the perceived effectiveness of the adaptive learning environment. The positive group shows a mean of 52% while the ambivalent group shows a mean of 40% producing a large effect size of 1.5. Guidance path (positive=51%; ambivalent=47%) and progression (positive=51%; ambivalent=45%) showed a similar trend producing effect sizes of .48 and .74, respectively.

LIMITATIONS

There are a number of limitations that moderate the possible analyses, methods and outcomes in this study. First and probably most important is the fact that responding student samples were extant so that there is no assurance that the responses represent the respective universities' student populations. Additional limitations arise from the fact that non-respondents contribute to sampling bias in the results. Further, adaptive learning is an evolving initiative that requires evaluation over an extended time period. This study was conducted at a single point in time and does not index the evolving nature of adaptive learning. The Likert scale format used to index student reactions limits the study because of the categorical nature of their required responses, essentially ignoring the qualitative aspects of the learning climate involved in this modality. In some cases, the lack of item response variability may have attenuated relationships, thereby impacting the latent attitude dimensions identified by the investigators. Finally, adaptive learning is a generalized concept that resists a specific definition. Therefore, it is entirely possible that the students in this study were responding to many various idealized models of what happens when they learn adaptively. Moreover, RealizeIt represents one potentially idiosyncratic category of adaptive learning platform based on Baysian prediction and machine learning.

DISCUSSION: ADAPTIVE LEARNING—IT'S ABOUT TIME

In our increasingly diverse society, adaptive learning increases student flexibility and the opportunity for achieving college success. Unfortunately, in our country the chances of educational success are not evenly distributed. Consider the fact that only one in ten students in the lowest economic quartile is expected to obtain a bachelor's degree while those who live in the top quartile have a seven in ten chance of college graduation (Korn, 2015). Over the past decades that needle has moved very little with students having to assume increasingly larger college debts that place them at a further economic disadvantage. However, financial resources comprise just one of the many difficulties that low income students face. Lifestyles involving work, family, time demands, medical care, and many other things prevent students from attending college on a regular basis because they simply do have the time or the means to devote to education. They live in a condition that Mullainathan & Shafir (2013) term *scarcity*—simply too many needs and not enough resources. Scarcity forces trade off thinking and reduces students' cognitive bandwidth and fluid intelligence. There appear to be common elements for poverty and the concept of scarcity that impact a student's ability to succeed in school. First, students are forced to tunnel—that is they are forced to concentrate on one thing to the exclusion of everything else. For instance, because students may have to arrange for child care, they may become unable to deal with anything else. Consequently, they have to let school work slide and are unable to attend class regularly. We have all had to tunnel at one time or another, establishing priorities whereby some things just did not get done. These students simply have no slack in their lives with respect to meeting their responsibilities. The lack of financial slack is a particularly burdensome problem. For instance, the inability to buy textbooks until student loans come in prevents overburdened students' from maintaining proper class achievement. The tech savvy students may find a solution, but those living in scarcity will have a much more difficult time because they lack equivalent access to technological resources. Without belaboring the point, Mullinathan and Shafir (2013) make a compelling case for how quickly these students will fall behind the curve such that dropping the course becomes the optimal decision.

Students living at or near the poverty line are not the only ones who must confront the scarcity phenomenon. In contemporary society, many individuals must weigh the opportunity costs against the value add of a college education. Certainly, there is a financial benefit to be gained by those who invest in a college credential, but entering and completing a traditional higher education program is simply not an option for those who must continue working to survive. They have neither the time nor flexibility to pull up roots and come on campus. Therefore, the campus must come to them through initiatives such as online programs. This does not completely solve the problem, however, because many of online courses are grounded by the semester or quarter structure with time constraints and fixed deadlines. Often these programs lack flexibility. Learners are confronted with additional, confounding factors. Our society is awash in information—some of it accurate and some of it misleading (Wurman, 1989; Wurman, 2001). A case in point is the recent controversy regarding fake news on the Internet (Maheshwari, 2016). Seife (2010, 2015) has termed this phenomenon *virtual unreality* and *proofiness*, situations in which data (often big data) are manipulated in ways that purposely mislead. Consider this quote by Taleb (2012):

> *There is a nasty phenomenon called "big data" in which researchers have brought cherry-picking to an industrial level. Modernity provides too many variables (but too little data per variable), and the spurious relationships grow much, much faster than real information… (p. 418)*

Or this quote by Powers (2011):

> *Tap, tap, tap, tap, tap, tap… Imagine you're in a gigantic room, a room so spacious it can comfortably hold more than a billion people. In fact, that's how many people are there with you right now.*
>
> *Despite its size, the room is ingeniously designed so everyone is in close proximity to everyone else. Thus, any person in the room can easily walk over to any other person and tap him or her on the shoulder.*
>
> *As you move around the room each day, this is exactly what happens. Wherever you go, people come up to you and tap you on the shoulder. Some tap gently, some firmly, but they all want the same thing: a little of your time and attention. (p. xi)*

There is simply too much coming at us, creating an overburdened informational environment for virtually everyone in contemporary society.

The University of Central Florida and Colorado Technical University, although demographically dissimilar, have addressed this problem by providing an adaptive alternative to the traditional educational structure (Dziuban, Moskal, Cassisi, & Fawcett, 2016). Adaptive learning is an alternative that has the potential to provide some learning latitude for students living in poverty, but also for those who face the pressures of the contemporary world of work and family responsibility. Adaptive learning also provides an alternative that takes into account and can incorporate the knowledge that adult students have from attendance in previous institutions, workplace training and development, and military training. The curriculum is altered into modular structures so that students can navigate a course according to the demands of their educational needs and lifestyles. Adaptive design provides to students who fall behind multiple options for getting back on track. In fact, within certain constraints, there is much less chance of falling behind in adaptive learning. Although there are many confounding factors for students living in scarcity, the big one is time to accomplish the work. Fundamentally, adaptive learning is about time (Adam, 2004; Norberg, Dziuban, & Moskal, 2011). Time to reach competency. Time to reflect. Time to assess. Time to practice and revise. Time to complete.

With adaptive learning, the temporal dimension of education has been expanded by facilitating students' movement through courses at their own paces. Learning is a constant and time spent is the variable. This model originally proposed by Carroll (1953) is the fundamental premise of adaptive learning. Students are encouraged through continual feedback and assessment to achieve competency at their own progression rate. However, given students' longstanding experience with lockstep semesters or quarters, it is not difficult to imagine students might experience dissonance with this learning. One can easily see that the new "learn as you go" model might cause students some time management problems because they have to confront elements described by Adam (2008) as a "timescapes challenge."

1. Time Frame (Beginning and End)
2. Temporality (Direction and Process)
3. Tempo (Pace and Intensity)
4. Duration (Engagement and Progression)
5. Sequence (Order and Priority)
6. Temporal Modalities (Past, Present and Future Learning)

The time shift can be dramatic for both faculty and students, causing faculty to worry about teaching and students to worry about their learning. However, once accommodated, adaptive learning provides the latitude for almost any course modality and learning taxonomy (Dziuban, Moskal, & Hartman, 2016).

CONCLUSION

This research was an attempt to determine how students adjust and react to the newfound learning flexibility provided by adaptive learning and to compare those reactions by cross referencing the perceptions of learners from the two venues (CTU and UCF) compared in this study. After compiling the results, some conclusions seem warranted. First, the respondents' demographics are considerably different at the two institutions. Students at CTU are older, more likely to be female, less likely to represent minority groups, with a much larger percentage of them working full-time. In terms of responses to adaptive learning, the UCF students felt that the item sequencing was considerably easier than did the CTU students. Although there were some institutional differences, students at both universities gave adaptive learning high marks for educational effectiveness. However, a noteworthy finding was that a higher percentage of UCF students indicated that they had interacted with peers less in their adaptive learning course than they interacted with peers in non-adaptive courses. By and large, CTU students did not share this perception.

In spite of the demographic and student response set differences, the underlying dimensionality by which students evaluate their respective adaptive learning environments were identical. The comparison of scores on those dimensions across the universities reveals that CTU students were more positive about the adaptive learning environment while UCF students were more positive about the learning guidance provided by the system. Members of the two groups were in agreement regarding their progression though the courses. When students from both universities were clustered by whether or not they felt they had learned effectively in an adaptive environment, 25% of this cross-university student cohort expressed considerably more ambivalence regarding the adaptive learning experience, responding with significantly lower ratings regarding the learning environment, guidance and progression.

The results of this study indicate that students from diverse demographic and educational backgrounds are able to make a seamless transition to the adaptive learning environment. Most respond positively to the added flexibility and opportunities for reinforcing their knowledge acquisition. In the years to come it may well be that of all the recent innovations in instructional technology, the affordances provided by this modality offer the best promise for leveling the educational playing field and eventually the economic disparities as well, deepening the student talent pool in every community.

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APPENDIX A

REALIZEIT STUDENT SURVEY

Q1 This semester, your class has used the Realizeit adaptive learning system to cover some or all of the course content. We would welcome your input regarding this system, specifically when considering a comparable course that did not utilize Realizeit.   Please consider only your experience with the Realizeit learning content when answering the questions below. This survey should take approximately 10 minutes of your time. You are free to omit any questions you are not comfortable answering and can stop this survey whenever you choose. Your answers will be aggregated with the class as a whole and you will never be identified in reporting this research. However, UCF is considering the Realizeit system for additional courses and your answers regarding your experiences can help us determine how to provide students with the best quality instruction in the future. Thank you in advance for your thoughtful comments and suggestions!

Q2 How would you rate the difficulty of the following aspects of the Realizeit content portion of the course:

	Too Difficult (1)	Somewhat Difficult (2)	Neither Easy nor Hard (3)	Somewhat Easy (4)	Too Easy (5)	I'm not sure (6)
The sequence of items on the "learning path" (4)	❍	❍	❍	❍	❍	❍
The learning material used to teach this course (5)	❍	❍	❍	❍	❍	❍
The questions asked during this course (6)	❍	❍	❍	❍	❍	❍

Q3 Overall, Realizeit helped me learn the course material better than not having Realizeit.

- ❍ Strongly Disagree (1)
- ❍ Disagree (2)
- ❍ Neither Agree nor Disagree (3)
- ❍ Agree (4)
- ❍ Strongly Agree (5)
- ❍ I'm not sure (6)

Q4 How often did you follow the suggested "Next Steps" path in Realizeit?

- ❍ Never (1)
- ❍ Rarely (2)
- ❍ Sometimes (3)
- ❍ Quite Often (4)
- ❍ Always (5)
- ❍ I'm not sure (6)

Q5 How much time did you spend in Realizeit compared to a class without Realizeit?

- ❍ Much Less (1)
- ❍ Less (2)
- ❍ The Same (3)
- ❍ More (4)
- ❍ Much More (5)
- ❍ I'm not sure (6)

Q6 How easy were the following Realizeit features to use:

	Very difficult to use (1)	Somewhat difficult (2)	Neutral (3)	Somewhat easy (4)	Very easy to use (5)	I never used this (6)
The "learning path" (1)	❍	❍	❍	❍	❍	❍
The "guidance panel" (2)	❍	❍	❍	❍	❍	❍

Q7 Did you experience any technical issues with Realizeit?
- Yes (1)
- No (2)

Q8 If yes, what technical problems did you experience? (Please ignore if you had no problems)

Q9 Technical support helped me solve any issues I had while using Realizeit.
- Yes (1)
- No (2)
- I did not contact technical support for the issues I had (3)
- I did not have any technical issues (4)

Q10 How helpful did you find the "guidance panel" supplied by Realizeit?
- Extremely Unhelpful (1)
- Unhelpful (2)
- Neutral (3)
- Helpful (4)
- Extremely Helpful (5)
- I did not use the guidance (6)
- I do not know what the guidance is (7)

Q11 Realizeit provided me with the necessary feedback to help me stay on track with the course objectives.
- Strongly Disagree (1)
- Disagree (2)
- Neither Agree nor Disagree (3)
- Agree (4)
- Strongly Agree (5)

Q12 The instructions in Realizeit were clear.
- Strongly Disagree (1)
- Disagree (2)
- Neither Agree nor Disagree (3)
- Agree (4)
- Strongly Agree (5)

Q13 Please indicate to what level you agree or disagree with the following statements:

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)	I'm not sure (6)
The ability levels reported by Realizeit were accurate (1)	❍	❍	❍	❍	❍	❍
The Realizeit system became personalized to me over time (2)	❍	❍	❍	❍	❍	❍
The grading accurately reflected my knowledge (3)	❍	❍	❍	❍	❍	❍
Realizeit's assessment exercises were effective in measuring my learning (4)	❍	❍	❍	❍	❍	❍
Realizeit increased my engagement with the course content (5)	❍	❍	❍	❍	❍	❍
Realizeit was easy for me to use (6)	❍	❍	❍	❍	❍	❍
Given a choice, I would take another course using Realizeit (7)	❍	❍	❍	❍	❍	❍

Q14 How often did you interact with other students compared to a class not using Realizeit?
- ❍ Much Less (1)
- ❍ Less (2)
- ❍ About the same (3)
- ❍ More (4)
- ❍ Much more (5)

Q15 What method(s) for interacting with others in the course do you prefer?(Check all that apply)
- ❑ Discussion boards (1)
- ❑ Live chat sessions (2)
- ❑ Live whiteboard (3)
- ❑ Virtual conferences with a group (4)
- ❑ Other: (5) ____________________

Q16 How much interaction with other students do you prefer?
- ❍ None (1)
- ❍ A little (2)
- ❍ No preference (3)
- ❍ Some (4)
- ❍ A lot (5)

Q17 What did you like most about Realizeit?

Q18 What did you like least about Realizeit?

Q19 How could your experience with Realizeit have been improved?

Q20 Your age (Please enter a number such as 20, rather than the word 'twenty'):

Q21 Your gender:
- ❍ Male (1)
- ❍ Female (2)
- ❍ Prefer not to answer (3)

Q22 What is your academic standing?

- Freshmen (1)
- Sophomore (2)
- Junior (3)
- Senior (4)
- Graduate (5)
- Other (6)

Q23 Which ethnicity best describes you?

- American Indian / Alaska Native (1)
- Asian (2)
- Black / African America (3)
- Hispanic / Latino (4)
- Multi-racial (5)
- Native Hawaiian / Other Pacific Islander (6)
- White (8)
- Prefer not to answer (9)

Q24 What do you expect your grade to be in this course?

- A(-) (1)
- B(- / +) (2)
- C(- / +) (3)
- D(- / +) (4)
- F(- / +) (5)

Q25 Including this semester, how many fully online courses have you taken? (Please enter a number such as 2, rather than the word 'two')

Q26

	0 - I'm not working (1)	1-9 hours (2)	10-19 hours (3)	20-29 hours (4)	30-39 hours (5)	40+ hours (6)
Approximately how many hours a week are you employed? (1)	❍	❍	❍	❍	❍	❍

Q27 How many credit hours are you enrolled in this semester?
❍ 1-3 (1)
❍ 4-6 (2)
❍ 7-9 (3)
❍ 10-12 (4)
❍ 13-16 (5)
❍ 17-19 (6)