Adapting to Learn, Learning to Adapt

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The Next Big Thing

Adaptive, or personalized, learning is becoming the next big thing in online education. By providing each student with a custom, personalized path through courses and tracking both content covered and level of attained mastery, adaptive learning platforms hold great promise for enhancing student learning and success. Adaptive course content is organized as a set of nodes in a learning path. Each node presents students with content and embedded assessments, the results of which determine the recommended next node. Students can also self-select learning nodes to attempt but must prove mastery to continue moving forward.

Adaptive learning lets you address why and how students learn, as well as their preferences for interacting with course content.

Tammy Muhs, Associate Lecturer, Mathematics

Adaptive learning platforms fall generally into two categories: those that come with vendor- or publisher-created content, and those that enable institutions to create their own content. Like learning management systems (LMSs), adaptive platforms continuously track in-course student actions and outcomes. Although assessments can be frequent in an LMS-based course, they are generally continuous in adaptive environments. This provides a more nuanced and detailed view of students’ levels of content mastery. It also allows instructors to provide real-time support for students who may need assistance or additional challenges for those who are succeeding. Data captured from students’ progression through the learning path can also help instructors or course designers detect parts of the course that need revision or, alternatively, are most helpful for students.

A Strategic Approach

The University of Central Florida (UCF) has been engaged in online learning for more than two decades, and over that time span we have designed and developed nearly 1,900 fully online courses and over 1,700 blended learning courses, with consistently high levels of student success and satisfaction. The motivation to explore adaptive learning was based on the belief that a combination of well-designed courses and a capable adaptive learning platform could lead to increased rates of student success in courses that have traditionally had unacceptably high levels of D and F grades and course withdrawals. In some cases, such as college algebra, these are gateway courses in which students must succeed in order to be admitted into STEM or other majors. The massive amounts of data captured in adaptive learning courses also provide our faculty and assessment staff with new opportunities for research on ways to better design courses and to foster improved student success.
We were also attracted to adaptive learning by other possibilities. One was the potential to actually track the progress of student learning rather than continue to rely on grades, which may be a poor proxy for knowledge attainment. Another was the possibility of replacing the traditional “time constant, learning variable” model with one in which learning is constant and time variable, as demonstrated by Carroll and in various Khan Academy experiments. A third was to explore innovative teaching strategies. For example, in the pilot adaptive college algebra course, the instructor is creating content and assessments relating to individual students’ fields of study in order to make the material more relevant and increase student motivation. We are also exploring the effectiveness of structuring the presentation of content to students in a format most closely associated with their preferred learning styles and success rates (e.g., as text, graphics, video, etc.).

Our selection of a primary adaptive learning platform (Realizeit) was based on the desire by our faculty and online learning support staff to design and create our own adaptive course content. To date, we have built and tested courses in general psychology, pathophysiology, college algebra, and statistics. Outcomes from these pilot courses have been very promising and will be discussed further below.

Both our LMS and adaptive learning platform run in the Amazon cloud. Students access their adaptive courses through our LMS, and the two are transparently integrated by means of the Learning Tools Interoperability (LTI) standard. This arrangement combines both adaptive and LMS capabilities, providing a richer learning environment than either alone.

Our selection of a primary adaptive learning platform involved in-depth analyses of adaptive products from multiple vendors by academic administrators, faculty members, and both instructional design and IT staff. After more than two years of pilot work with adaptive learning, we are reasonably confident about how faculty and students respond to teaching and learning in an educational environment that is personalized and adaptive. In addition, we have been able to estimate what UCF will have to do in order to scale adaptive learning and to help it achieve its potential for improving student success and progression on a broader scale.

Designing and developing effective adaptive learning courses is not without challenges. One faculty member compared the effort to writing a textbook. Although the platform can ingest content from existing sources, organizing it into the learning map and developing assessments can be time-consuming. To alleviate this burden on the faculty, UCF’s Center for Distributed Learning hired instructional designers and adaptive course developers to reduce the workload on faculty. Other support is provided to faculty as needed, such as a mathematics graduate teaching assistant to work alongside the faculty member. The Center for Distributed Learning engages academic departments and colleges in our adaptive learning efforts, rather than individual faculty members, in order to ensure departmental buy-in and a longer-term return from investments in adaptive course development.

Everyone associated with our pilot adaptive learning courses—students, faculty members, online learning staff, and senior administrators—is enthusiastic about both the initial results and the long-term potential. Of course, evaluating the impact of adaptive learning on students, faculty, and the institution is a long-haul proposition and can only be accurately assessed after the modality settles into the university culture. The pressing question of improved student success will take some time, and as Levitt and Dubner warn us, attributing a particular cause to a particular effect can be tenuous. Taleb warns us not to confuse no
evidence of impact with evidence of no impact. They are two very different outcomes, and interchanging the former for the latter can cause us to overlook meaningful results that would add value to strategic and policy decisions.

Is Adaptive Learning a Solution in Search of a Problem?

The answer to that question is probably not because adaptive learning has the potential to address at least two problems in American higher education: modeling learning taxonomies and scarcity.

Learning Taxonomies

A casual literature search will identify multiple learning taxonomies where higher knowledge levels subsume all those below them. Recently, however, Feldstein used this approach to critique some adaptive learning vendors who, he suggested, tout adaptive learning as a replacement for instructors. He analogously refers to the stages that automotive technology must undergo before a vehicle is considered fully self-driving. The third of these stages is when the vehicle assumes most of the driving function but still requires periodic driver intervention—a dangerous situation where driver inattention can lead to catastrophic consequences. However, when applying this metaphor to adaptive learning, level three seems optimal because the system manages several components of student progress through the course content while necessitating and facilitating instructor monitoring and intervention.

Floridi addresses the issue of replacing instructors when he contends that education is primarily driven by contemporary information and communications technologies (ICTs). Because of these readily available educational resources, he argues, the real problem is not how to teach but what to teach (curriculum framework) and, more importantly, why. The result of his thinking is a framing of learning into four stages that migrate from acquired information to ignorance:

1. **Information**: There are things a student knows (e.g., how to compute a correlation).
2. **Incipience**: There are things a student does not know (e.g., whether it is the appropriate measure of relationship).
3. **Uncertainty**: There are things that a student is not quite sure he or she knows (e.g., whether the correlation is computed correctly).
4. **Ignorance**: There are things students do not even know that they do not know (e.g., correlation is a function of progressive cross-products and covariances and can be expressed in geometric terms).

Floridi’s reasoning “aligns” with adaptive learning platforms because their fundamental purpose is to convey information in a carefully planned sequence either designed by the instructor or provided by the vendor. Because most of the currently available systems incorporate some form of machine learning that continually sequences and redesigns learning paths for students, the limit of their knowledge (their incipience) becomes an integral part of the adaptive learning process. By repeatedly verifying understanding and competency, adaptive learning resolves students’ uncertainties though practice, repetition, and application of acquired knowledge to novel situations. Finally, because adaptive learning is prescriptive (some may argue deterministic), it can resolve students’ ignorance of content by directing them through optimal and personalized learning paths to knowledge and information of which they were unaware. Floridi’s formulation addresses an educational environment awash with information, where
dispensing is replaced by curating. Although effective teachers respond to each one of the four stages, adaptive learning systems function quite well as assistive technologies by augmenting the teacher’s ability to manage individual students efficiently. Unlike driving systems, instead of posing a threat when faced with student inattention, instructors assist learning with autocatalytic technology assistance. To be sure, current platforms are, in many cases, inadequate with respect to performance and integration into higher education. However, they do offer promise for supporting students and teachers through the various important stages of learning. Floridi summarizes this when he discusses the potential of ICTs that encompass adaptive learning:

ICTs may allow a degree of didactic customization unprecedented in non-elitist contexts: the personalization of the educational experience for millions of individuals. We know that ICTs are the ideal tools to monitor individuals’ behavior. For once, such a power can be put to good use. Yet all this is a matter of delivery, policies, methods and technologies. If it is taken to be a solution of how to educate Generation Z and the others which will follow, then we are mistaking the painkiller for the cure.

Scarcity

Mullainathan and Shafir highlight another problem in contemporary society for which adaptive learning can be effective: scarcity. Scarcity can be defined as having far more needs than resources. Consider the lives of students living at or near the poverty line—they may be working two part-time jobs with no benefits and so are unable to take a full course load. Health care costs are a significant burden. They may also have childcare expenses in addition to tuition and others costs, such as textbooks. Most likely they borrow money to attend school and may be unable to search for additional financial assistance because of time or resource constraints. Transportation is an additional problem; public transportation creates a time crunch, while a car adds additional expenses.

These students are caught in what Mullainathan and Shafir term the scarcity trap that depletes their cognitive bandwidth. They have comparable abilities to their more affluent peers, but the demands and stresses of their lives prevent these young people from effectively using those abilities. They have no slack, either cognitive or financial, in their lives, causing them to juggle so many things that they cannot devote the time and effort required by their courses.

This scarcity structure is fragile and requires a monumental balancing act. For instance, if a student’s car needs repairs, the entire system can collapse: The car is needed to get to work and school, but if the student pays the car repairs, he cannot make rent or tuition payments. If the student takes public transportation, he risks being late or getting fired, adding even more stress. This balancing act forces the student into a situation where he must tunnel—that is, concentrate on the immediate problem and ignore everything else.

What does this have to do with higher education and adaptive learning? Mullainathan and Shafir explain:

What happens when a loaded and depleted client (student in our world) misses class? What happens when her mind wanders in class? The next class becomes a lot harder. Miss one or two classes and dropping out becomes a natural outcome, perhaps even the best option, as she no longer really understands much of what is being discussed in 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. …Linear classes that must not be missed can work well for the full time student; they do not make sense for the juggling poor.
In contrast, consider an adaptive learning course with modules supported by learning nodes and a go-at-your-own-pace design. Many adaptive platforms ask students to specify their degree of uncertainty about the content of each module and then, based on that estimate, conduct a prior assessment of their knowledge state. Using this predetermination, an adaptive learning course can place a student at the optimal starting point corresponding to her estimated competency level. Students living in scarcity can achieve success and progress at a rate that will maximize their potential for course completion. Should a student stumble in a course, he can be redirected to knowledge or concepts that require reinforcement before they progress. Because many adaptive systems can determine a student’s preferred or optimal content delivery formats, they can present material that corresponds to those preferences. Students may take longer to complete the course, but, given that they eventually succeed, is time the significant factor? A recent article in *Inside Higher Ed* indicated that students from the lowest socioeconomic quartile in the country have a 9% chance of graduating from college. A large percentage of them are coping with scarcity that is the major contributor to their lack of academic success. At its full potential, when running properly and with faculty support, adaptive learning can help address this real problem in our country.

**The Student Perspective**

In the adaptive learning pilot phase at UCF, four faculty have redesigned five of their fully online courses so that the content is contained within the adaptive learning platform. Undergraduate courses included General Psychology, College Algebra, and Pathophysiology for Nursing Practice. Graduate classes have included Statistics for Educational Data and Pathophysiological Basis for Advanced Practice Nursing.

The participating faculty members were optimistic about using adaptive learning. General Psychology is a general education course with many sections that can often be taught by adjuncts. The professor saw adaptive learning as a way to provide more-uniform content across all sections. Finding a way to maintain quality and personalize the experience for large online classes increases access, allowing more students to be accommodated.

The mathematics instructor envisioned adaptive learning as a means to address the challenge of student success in the sequence of math courses required for students who wanted to enter STEM disciplines. The interwoven nature of adaptive courses allows the progression from college algebra to calculus to be connected as a continuous curriculum rather than a series of discrete courses. This approach affords students the opportunity to practice and reinforce concepts that they may have encountered earlier in the sequence, without impeding the progress of those students who can progress through the courses more quickly. It also builds in effective remediation in that the entire body of content is accessible to students at any point in their journey through the math course sequence. In addition, the ability of the adaptive platform to “learn” how students best learn—both in terms of presentation format and of content relating to their individual disciplines (hospitality, engineering, etc.)—may also help increase student success in these courses. With all course content contained within the adaptive learning platform, the textbook could be eliminated, reducing costs to students.

In nursing, the instructor initially used the adaptive platform to integrate authentic case studies for the pathophysiology course. The adaptive nature of the system allowed each case study to be unique, as opposed to having each student work on an identical scenario in paper form in a face-to-face format. Having students who were skilled practicing nurses also meant that many came with a depth of
experience in their specific area. Working in the adaptive environment, they could essentially “test out” of those areas in which they were already expert while focusing on those topics where they needed additional instruction or review.

Statistics is a subject that is often met with trepidation by students. The statistics professor was able to help students overcome their concerns by providing a means for them to more efficiently identify the areas where they needed reinforcement and more quickly progress through content they already knew. In addition, the system provided valuable information that allowed the instructor to know where students encountered difficulties so that she could reinforce those topics and answer targeted questions to help individual students.

Roughly 80% of UCF students have taken at least one fully online or blended class, so the majority are experienced with learning online. UCF uses the Instructure Canvas LMS, which we have branded “Webcourses.” UCF students access their adaptive courses through the Canvas LMS, which provides faculty members and course designers all of the tools that both platforms afford. Individual courses are designed with a similar structure through which students can access course announcements, the gradebook, modules, assignments, and discussions. Through the use of the IMS LTI standard, locally developed and third-party tools can be seamlessly integrated within the LMS environment.

Each fall and spring semester of the two-year pilot, we surveyed students regarding their reactions to the adaptive learning interface and their experiences in the adaptive learning environment. Students have been positive regarding the system and how the approach influences their learning (see figure 1), with the majority indicating that they would take more adaptive learning courses if given the chance.

——Julie Hinkle, Assistant Professor, Nursing

Outcome assessment in the adaptive learning environment has the potential to be more authentic, contextual, and relevant for students who must make important decisions that go beyond a collection of facts.
Student comments reflected on the personalization possible with this instructional method. Students appreciated being able to go at their own pace—taking extra time to review material they were learning, while moving more rapidly through content already mastered. They also appreciated that the system determined their knowledge upon entering a module, placing them within the content appropriately and in some cases presenting them with the best format for their learning. The majority of students appreciated the personalization the method provided.

Students’ challenges regarding adaptive learning indicated a dissonance between a “linear” course and an adaptive one. Students wanted more practice problems, examples, and additional instructional methods, such as videos. Courses needed to have realistic weekly time and workload expectations. Although adaptive learning allows students to progress at their own pace, the nature of semesters and course rhythms meant that there was a time schedule for exams that required students to complete a certain amount of work beforehand. In addition, because the adaptive algorithms incorporate practice time on task as well as performance metrics, students found it difficult or impossible to obtain a perfect score on assessments. This created a discontinuity with their mindset of what traditionally constitutes “grading” exercises. Faculty had to address these concerns and, in some cases, adjust algorithmic scoring ranges, while still providing the system with the data it required to accurately direct students.

The Faculty Perspective

At its full potential, adaptive learning forces the rethinking of structure, organization, and timing in contemporary higher education, as reflected by the four faculty members who converted their courses to this modality. They commented on planning, implementing, assessing the redesigned format, and clarifying instructional roles. Because adaptive learning is primarily self-paced, they indicated that the course design and content-sequencing processes required extensive planning and several iterations in order to produce a prototype adaptive course. That extended planning process, however, caused them to predict some possible impacts of adaptiveness on higher education over time. The faculty members foresaw a coming textbook independence, creating the need for increased content connectedness around student-centered courses and programs. The psychology instructor described an autocatalytic learning environment characterized by continuous feedback cycles that increase learning energy as the course progresses.

Curriculum implications were equally far-reaching. For instance, effective learning progress required considerable reorganization into a multilevel course design. Adaptive learning depends on a modular structure, so understandably it becomes competency based, requiring consideration of prior-learning status. These faculty members believed—although it seemed counterintuitive—that different courses can be effectively taught simultaneously—with the distinct possibility of multiple starting and ending points—while also being highly responsive to student needs. In their view, the adaptive curriculum alleviates time pressures on students, thereby mitigating traditional frustrations caused by conventionally structured
courses (i.e., learning deficits accrued by missing a class and submission deadlines). The entire teaching cohort indicated that adaptive learning demands assessment be an integrated component of the curriculum and, because of that, forces higher-level thinking and learning processes.

However, because of shortened and lengthened learning cycles, the faculty members raised important challenges as well. For instance, how will teaching in an adaptive format impact faculty load? Further, assessment undergoes major transformation in adaptive learning courses. Phrases such as “just-in-time embedded assessment” and “scaffold-based skill progression” were recurring themes. The nursing instructor saw the case study format as most effective and authentic because it forces continuous revision that morphs into adaptive assessment. One faculty member raised the notion of “assessment-free learning”—a term that she indicated was a metaphor for assessment as an integrated component of the learning process. Real-time assessment raised the possibility of adaptive analytics where instructors might obtain an indication of which students were experiencing difficulty with the content very early in the course. These developments caused the faculty members to conclude that the role of the instructor changes dramatically in an adaptive teaching protocol. Primarily, they saw themselves as resource curators responding to and integrating student performance and progress in a system that checks repeatedly for understanding, enabling them to become more effective at gauging and responding to individual student learning progression.

As with any new teaching and learning technology, start-up problems are to be expected. Challenges with integrating the adaptive learning platform and the LMS with grading algorithms quite often created student frustration. One instructor reported that the adaptive platform also amplified technical problems in some course start-ups. From an instructor’s perspective, designing and developing an adaptive learning course is a demanding task requiring extensive instructional technology and design support. However, in almost all instances the instructors encountered considerably fewer problems than they anticipated.

The faculty members’ consensus was that adaptive learning is best suited for courses that have a hierarchical structure—where there are interdependent learning and skill requirements. They pointed out that adaptive learning platforms should be considered an instructional tool and that effective use of that tool is the primary consideration. However, these faculty members expressed the opinion that adaptive learning is the future of higher education—one instructor even indicating that she planned to convert all of her courses to this format.

What the Future Might Hold for Adaptive Learning

In this section we discuss two possibilities for the future: how adaptive systems might evolve, and a new learning diagnostic model. Because we termed adaptive learning “the next big thing,” the implication is that it is new; however, this is not the case. Adaptiveness in some form has reflected the thinking of scholars for years. The concept is a fundamental element of diverse disciplines ranging from information science to societal development and, of course, education. For reasons stated earlier, adaptive learning has been embraced as a possible solution to learning challenges students encounter in their college careers. We discussed two among many: targeting learning activities to student cognitive levels, and avoiding the pitfalls of the scarcity trap.
Thinking Machines

Historically, the stumbling block for adaptive learning has been the availability of effective technology to support the process. However, just as the technologies for adaptive testing (e.g., item response theory) caught up to the formulations of early developers, adaptive learning systems have made significant progress in recent years. In addition to many unique features, these systems have commonalities: baseline calibration, progress monitoring, recommendation engines, competency assessment, feedback cycles, and instruction tailored to student preferences. This combination of elements, however, suggests that each platform has distinct advantages and disadvantages for particular institutional contexts. In a recent conversation with a UCF department that was considering two competing adaptive platforms the statement was made that we should conduct a comparative study and then adopt the clear winner. Unfortunately, this is rarely the outcome. Most likely platform A does many good things, as does platform B. However, both may underperform in some areas as well. Therefore, when considering a system to support an adaptive learning initiative, institutions should be able to answer an important anthropomorphic question: “How does this system think?” More simply stated, “Do I have a clear understanding of this program’s adaptive mechanism?”

When Tyton Partners asked platform providers to describe their adaptive procedures the results were diverse. Where possible, we excerpted their responses:

- Smart tutor adapting
- Big data and knowledge-space theory
- Content timing
- Intelligent tutoring
- Dynamic profiling
- Difference engine
- Combining personalized and adaptive learning
- Knowledge anchoring and retention
- Two-sigma solution
- Big data and algorithms
- Adaptive standards
- Inferred predictive learning analytics
- Continuous progress assessment
- Imbedded learning science
- Learning measurement system
- Analytics

Even as adaptive providers proliferate and develop separate approaches to workable systems that ultimately compete with each other for market share, there appears to be a looming development in the area of artificial intelligence (AI). A recent special report in the Economist, “The Return of the Machinery Question,” documents remarkable progress in AI. After many years of false starts, a breakthrough has appeared, built on a foundation of layered neural networks. The progress has been so rapid that the old question of the machines’ becoming aware and posing a threat to humanity has once again arisen.

Adaptive learning has not been overlooked by the AI community. The special report took dead aim at it: “At the moment, adaptive learning works best in areas where large numbers of pupils have to learn the same material and a lot of data can be collected.”

The report goes even further in proclaiming the potential of AI as a platform for new learning models:

In a report published in February, Pearson suggests that AI could make learning “more personalized, flexible, inclusive and engaging.” Such systems do not replace teachers but allow them to act as mentors rather than lecturers.
Even outside the AI community there is broad consensus that technological progress, and artificial intelligence in particular, will require big changes in the way education is delivered, just as the Industrial Revolution did in the 19th century.

Clearly, we are in the beginning stages of understanding adaptive learning and how it interfaces with higher education. Presently, we do this by considering the merits and shortfalls of a rapidly expanding cacophony of adaptive learning platforms. However, the future may be radically different, where layered neural networks can be trained to support particular courses or possibly learn by themselves. If this becomes the case, educators will most certainly be relying heavily on colleagues in computer science, machine learning, and data mining.

**Real-Time Predictive Analytics**

Adaptive learning intersects with another innovation in education: predictive analytics. This movement has been continuing for a number of years; there appear to be three major approaches:

1. Big data prediction
2. Off-the-shelf platforms
3. Institutional initiatives

Predictive analytics mechanisms have some similarities to adaptive learning. They attempt to identify—early in their courses or programs—students who are at higher risk of not succeeding academically and offer assistance to them or work with institutions to develop guidance and intervention. Throughout this area one principle is well understood: There are critical points in students’ academic lives that, if successfully traversed, create a much better opportunity of obtaining a degree. One project that focuses on helping students do this is “Reimagining the First Year” by the American Association of State Colleges and Universities (AASCU). This project concentrates on the freshman year in college, when students are most likely to withdraw. The premise is that the earlier potential problems can be identified, the better the chances for student success.

However, with the advent of adaptive learning there appears be another possibility for identifying students who are in danger of not succeeding in their courses: adaptive analytics. Most adaptive learning systems operate in real time, embed assessment procedures, provide immediate feedback, and offer guidance to students. That they begin assessing students immediately is the key to adaptive analytics.

For example, see figure 2, which shows the outcome scores for each of the eight modules in the adaptive general psychology course for the 278 students who succeeded and the 14 students who did not. The progression lines for the two groups are markedly different, and they diverge very early in the course. The mean for the successful students on module one was 9.3 (out of a possible 10 points) and 9.0 for the students who eventually failed to succeed. The respective standard deviations were .67 and .94—the two groups appeared roughly comparable and mean differences were not significant. However, by the module-two assessment the situation changed dramatically. The mean for the successful group was 9.5 while the unsuccessful students achieved an average score of 7.4—a 22% decline. Even more noteworthy was that the standard deviation in the successful group on module two was .40 compared to 3.3 for the declining 14 students—over 8 times larger. This indicates that not only did the successful group score closer to the maximum, but they were also very much like each other in their performance. However, as early as module two an adaptive platform can call immediate attention to the fact that the
unsuccessful group demonstrates a noticeable decline in performance. This decline continued so precipitously that by module 8 the means for the two groups were 9.1 and 1.2, respectively. The fact that adaptive learning platforms can enable instructors to identify students who are likely to encounter difficulties almost immediately is a distinct advantage for timely interventions, especially in large classes where monitoring may be more difficult.

![Graph showing module mean scores for successful and unsuccessful students](image)

**Figure 2. Module mean scores for successful and unsuccessful students**

**Conclusion**

It is risky to think of any new technology as a silver bullet, and this is certainly the case with adaptive learning. As with any new tool, adaptive learning provides a new set of capabilities and insights—and a lot of very useful data—that can be used to explore ways to increase student learning and success. And opportunities for experimentation are plentiful.

For example, we could explore new faculty engagement models in which teams of faculty design and develop adaptive course sequences, while other faculty members (perhaps aided by teaching assistants) monitor and facilitate course delivery. Because each student receives a fully personalized learning experience, we could experiment with scaling adaptive courses to larger enrollments, decreasing the marginal costs of educating students. And we have already mentioned opportunities for making adaptive courses “the textbook,” thereby reducing student costs. Adaptive course development costs could be further reduced by employing open-source content, licensing material from publishers, or multi-institutional collaborations. Finally, and perhaps most significantly, the massive amounts of data that are generated by adaptive platforms afford rich opportunities to engage faculty members and course developers in research on student learning and course design that can ultimately lead to greater levels of student success. One of the functions served by the grades assigned to students is to put a label on how much they did or did not learn. We can foresee a future where student learning can be both measured and assured, and where any and every student can legitimately earn an A.
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Citation for This Work


Notes

20. Ibid., 170–71.


27. Gates Bryant, “Learning to Adapt 2.0.”

28. Ibid.


31. See “Re-Imagining the First Year,” American Association of State Colleges and Universities.