# Section II

# Assessment Issues to Consider Before Adopting a Digital Platform or Learning Program

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The passage of No Child Left Behind in 2002 helped frame the virtual education choices schools now have. Promoted by the lobbying efforts of tech-friendly foundations such as the Bill and Melinda Gates Foundation and corporations such as Pearson, the emphasis on standardized tests and continuous student assessment contributed significantly to the demand for "ed tech" in schools. It takes computers to process the massive amount of test data schools are required to collect and report.

The tech industry and a host of self-interested vendors and corporations have further stoked the demand for computers by aggressively promoting virtual education over the last decade and a half.[1] The Gates Foundation and Chan Zuckerberg Initiative, in particular, have spent hundreds of millions of dollars to promote digital "personalized learning," a data-friendly approach to pedagogy that also demands continuous assessment.[2]

The No Child Left Behind testing regime is now widely considered to have been ill-advised and there is little, if any, credible research that indicates digital learning programs or virtual education are effective. Nevertheless, the COVID-19 pandemic has supercharged efforts to use digital technologies to reshape school programs.[3] Despite the public relations effort that presents digital technologies as the common-sense solution to the dilemmas posed by the pandemic,[4] it is important to recognize that digital technologies also pose significant threats to the schools and school communities that adopt them. The assessments programmed into digital platforms and learning programs may negatively shape student learning, subtly alter the curriculum, de-professionalize teachers' role, and appropriate and misuse student data unless school leaders make careful decisions.

To understand the nature of the problem, it is important to recognize that digital platforms and learning programs implement particular theories of learning and child development.

The learning opportunities these platforms offer to students are, therefore, necessarily determined by these theories, as are the assessments used to evaluate students' accomplishments.

Digital platforms and programs provide a variety of features that streamline assessments and save teachers time. For example, they may offer assessments, coordinated with content units, that automatically evaluate and record student performance. This is a mixed blessing, because the more that platforms and learning programs automate assessment and record-keeping, the more they limit teachers' ability to assess students based on their direct observation and impede teachers' ability to critique or correct judgments made by the software. At the same time, built-in assessment programs generate data that often flows back to parent companies that may use it for unknown purposes. To help school leaders make sound decisions, we have identified six key digital assessment-related issues for them to consider. Below we discuss the importance of each.

### Pedagogical theories embedded in digital platforms and learning programs shape the student learning environment.

Many digital platforms and learning programs rely on the same behaviorist theory of learning as did the "teaching machines" promoted for school use over 70 years ago.[5] In essence, the approach relies on the assumption that there is a uniform set of facts or skills that students must master, and that knowledge of these facts or skills can be broken into small elements and presented bit by bit to students, who can then learn each element and be tested on it. Students' ability to provide the required responses to assessment questions about each element is assumed to demonstrate their competency/mastery of the element, and therefore, "learning" is a process that repeats itself continuously until a student has "mastered" the presented elements.[6] While this kind of approach allows for students to move through the program at their own pace, it also assumes that children do not require a meaningful context for their learning.[7]

"Competency-based education" (CBE),[8] based on this hyper-rational behaviorist approach, is programmed into many digital learning platforms and programs, particularly so-called "personalized learning" programs. These programs embody tacit assumptions. The first is that their designers and programmers can effectively organize the fragments of information students are expected to master and program the assessment tools to measure whether or not they have been mastered. The second is that this programming "personalizes" learning for all the students. Given the diversity of students' backgrounds, needs, and learning contexts, these assumptions are unwarranted. While it is true that some children may quickly demonstrate "mastery" of the facts and skills defined in these programs by learning how to answer assessment questions correctly, it is also quite possible that because they have not learned those facts and skills in a personally meaningful context, they will not be able to apply their "mastery" in real-world situations. As a result, what they learn may be of little or no use to them—except to pass tests.[9] For example, a high school student who appears to have mastered all the required math competencies may not understand how the interest owed on their credit card debt compounds.

In contrast, when teachers help students contextualize learning through classroom tasks and discussions of their experiences, their understanding can deepen because they engage with the curriculum in a personally meaningful way. To the extent that a digital platform or learning program minimizes teachers' ability to contextualize learning for their students, assessment evidence of student learning may be illusory. Products that encourage teachers to contextualize students' learning and to conduct their own assessment of students' understanding may require more teacher time and effort than products that provide content and assessment. They are more likely, however, to facilitate meaningful learning and assessment.

### Assessments programmed into digital platforms and learning programs can shape and narrow the curriculum.

The assumptions of digital, competency-based education—that knowledge can be broken into logically structured elements, that student mastery of each of those elements must be continuously assessed, and that constant data reporting is necessary to ensure children's progress—inevitably narrows the curriculum and limits teachers' options. The assumption that acquiring a collection of small bits of discrete information and numerous discrete skills is the essence of learning necessarily also tends to exclude anything that cannot be reduced to a quantifiably measurable standard. The more that teaching and learning are shaped by the collection and use of easily quantifiable data points, the more limited the curriculum and definitions of "achievement" become, and the more likely that success will be defined by those things that can best be captured and sorted electronically.[10] Necessarily, students will focus their efforts to strive to succeed at those things.

In contrast, educators have for years developed approaches to curriculum to help children cultivate a wide variety of interests and skills difficult or impossible to quantify. To imagine alternatives and find creative solutions to problems. To interpret information based on sound reasoning. To develop personal identity and use knowledge in personally meaningful ways. And, to develop the interpersonal and social skills necessary to participate in and contribute to democratic civic life.[11]

It is obvious that children can learn much more in school than predefined skills. They can, for example, learn to be part of a classroom community in which academic knowledge, technical competence, social skills, and personal identity are also developed in the context of genuine engagement with other people.[12] For instance, children who learn about plant growth by cooperatively designing and cultivating a class garden and then eating the resulting fruits and vegetables have a vastly different learning experience than children who acquire information about photosynthesis in programmed bits and pieces, even if those facts are delivered by an amusing, gamified educational application.

Since human learning is often not sequential or even logical, narrowing children's education to the acquisition of one skill, fragment of information, or concept after the other in an apparently logical progression not only constrains their experiences, it can also undermine their ability to integrate what they have learned in real world situations (that is, to transfer their learning) and inhibit their achievement of broader educational goals.[13] Digital learning programs define how teachers, students, and administrators interact—by defining how they understand what "learning" means, what "counts," and what is important.[14] They also increasingly script the teaching and learning process, crowding out the kind of unanticipated teaching moments sparked by a student question or comment on which teachers capitalize even if it means detouring from their lesson plans. Such unplanned opportunities cannot be coded into any software.

Finally, the reality of forcing all children to learn and be evaluated via technology-mediated relationships with their teachers contradicts the rhetoric associated with personalizing education and responding to children's unique needs and interests—the rhetoric that has been used to promote digital platforms and programs. In other words, forcing all children to learn via digital means, with constant focus on assessment data and "mastery" as the definition of learning, can reasonably be seen as the opposite of child-centered or personalized. Digital programs that provide for more teacher latitude in organizing their curriculum and developing their assessements are likely to be better than those giving teachers less latitude.

## Opaque algorithms that may be biased run the assessments programmed into digital platforms and learning programs.

Any test reflects the values, assumptions, social positions, interests, or biases of its creators. In a simple example, a teacher described how seemingly innocuous language in a test question reflected the culture of the test creator and was incomprehensible to his students. The question asked students to identify which of a series of pictures was a "casserole." The teacher noted that although casseroles might be common in Iowa, where that particular test originated, his young students in inner city Texas had never seen one and could not answer the question.[15] Concerns that the language or examples used in standardized tests may discriminate against minority group students have dogged standardized testing for years.[16] They have led to calls for standardized tests to be replaced by locally derived assessments.[17] They have also caused parents nationwide to refuse to allow their children to take end-of-year summative examinations.[18]

Assessments built into digital platforms and learning programs magnifiy these concerns. Much like standardized tests, the assessment algorithms built into educational software are presented as "neutral" and "scientific," and to embody "truth" or fact.[19] They cannot be neutral, however, because they are created by people—and people are not neutral.[20]

Algorithms are much more problematic than standardized tests because they are central to the day-to-day functioning of the digital educational program. They are not limited to end-of-year summative assessments, but rather implement the regular formative assessments designed to mediate between teachers and children, and to influence children's experience of the curriculum. Algorithms are also less transparent than any physical assessment document. Unlike the example in which the teacher was able to flag the question about the casserole as inappropriate for his students, teachers may not even see the questions that their students are asked to answer. Yet some programs require teachers to, "in real time," adjust their teaching to the results that the algorithms report. Programs that feature "adaptive" or "personalized" learning bypass teachers completely and automate the instructional decision-making that teachers would ordinarily control.

Embedding instructional and other educational decisions in digital learning programs also reduces parents' ability to advocate for their children. Unlike with summative standardized testing, parents cannot opt out of the assessments embedded in the digital learning program the school has chosen. And unlike a traditional class in which parents can question teachers' decision-making if they have concerns, the more that instructional decisions are transferred to algorithms, the less parents are able to question. The teacher may not be able to explain how the algorithm works. To be clear, marketing materials for digital platforms and educational programs portray the role of their algorithms in determining what and how a child is taught as an advantage—but it is not.

Far from being "objective," algorithms reflect the myriad choices their developers make. They are vulnerable to significant and difficult-to-correct error.[21] An algorithm that assesses a student's level of understanding based on, for example, his or her pattern of responses, response times, and keystrokes generates conclusions based on a theoretical mathematical relationship between those raw data points and the student's psychological state of understanding. The key word here is *theoretical*. For example, essay scoring algorithms implement a theory that high-quality essays are characterized by grammatical features such as sentence length, vocabulary, spelling, and subject-verb agreement. Researchers analyzed automatic essay scoring programs (e.g., the Educational Testing Service's "e-rater" that is used to grade several statewide assessments, the Graduate Record Examination (GRE), and the Test of English as a Foreign Language [TOEFL][22]) by having them score nonsense essays composed of strings of sophisticated words and sentences that made no sense. The nonsense essays consistently received high, sometimes even perfect, scores.[23]

Companies' proprietary assessment algorithms are rarely, if ever, offered to external reviewers to analyze.[24] Therefore, the validity of the content and of the assessments those algorithms generate cannot be challenged by the students who are subjected to them. It must simply be accepted as "true."[25] The students' role is simply to "master" what is presented to them and accept the rulings generated by the algorithms.

*Far from being "objective," algorithms reflect the myriad choices their developers make.*

Automated grading and record-keeping are promoted as ways to decrease drudgery and increase teacher time with students. However, digital platforms and learning programs actually marginalize teachers by taking the critical matter of assessment and the content of conversations about learning largely out of their hands. For example, teachers may be unable to see how their students earned the designation of mastery of a skill or achieved a goal in some applications because the software, not the teacher, has determined the questions asked and the grades assigned. If the software and its assessments are biased and have limited validity, the teacher would never know. Neither would the children, their families, school administrators, employers, or anyone else who later gets access to the software's output. The more that a digital platform or learning program inserts itself into the relationship between students and teachers, the more opportunities there are for its output to be biased or flawed, and the greater the influence of those biases and flaws is likely to be on how students are taught and assessed. The less that it is programmed to do, the less problematic it is.

### Assessments in digital platforms that use predictive analytics, artificial intelligence, and machine learning can harm students in difficult-to-identify ways.

As companies experiment with artificial intelligence and machine learning to provide schools with predictive analytics, the dangers associated with the opacity of algorithms intensify. For example, in 2019, Instructure CEO Dan Goldsmith was discussing a new feature of the company's popular Canvas learning management system when he promised the ability to

> start making recommendations and suggestions to the student or instructor in how they can be more successful. Watch this video, read this passage, do problems 17-34 in this textbook, spend an extra two hours on this or that. When we drive student success, we impact things like retention, we impact the productivity of the teachers, and it's a huge opportunity.[26]

In fact, this "opportunity" puts children, parents, and teachers in a horrible bind. They have no way of knowing how the platform derives its recommendations, or how to evaluate their accuracy or worth. Their only option is to comply.

Georgia State University uses "big data" predictive analytics to identify students who may be at risk for dropping out. The *Hechinger Report* profiled a student who the software flagged as unlikely to achieve the 3.5 average he would need to apply to his chosen major, nursing, at the end of his sophomore year.[27] Although his average was close to the cut in his freshman year, his similarity to other students who had not made the cut led the algorithm to mark him as at risk of dropping out. As a result of counseling based on the algorithm's conclusion, he chose a related but less demanding major. At the time of the writing of the *Hechinger Report*'s article, he was on track to complete his degree in respiratory therapy. He did not drop out, but he also was pushed to abandon his original life and career goals.

The programming of predictive analytics may very well contain "equity blind spots."[28] As the *Hechinger Report* notes, these blind spots may reinforce historical inequities and direct low-income students or students of color into easier majors. It is also hard to know how students will respond to the predictions offered by the algorithms. How many students, rather than lowering their goals, completing their degrees, and leading happy lives (albeit with lower levels of accomplishment and income than they would have had if they had achieved their original goal), become discouraged by the dashing of their hopes and drop out?

In the Georgia State example, the university student made the final choice of his major. In K-12, the algorithm decides for students. For example, critics have questioned the validity of the predictions that replaced actual test scores on Britain's spring 2020 A-level exams, arguing that they discriminated by race and class and caused universities to withdraw offers of admission.[29]

Leaders of education technology companies are bullish about their growing ability to offer predictive analytics and to influence student behavior and outcomes. Instructure's former CEO, cited above, responded to concerns about his company's algorithms by asking, "Should we take those fears of what could go wrong and completely cast aside the potential to improve the teaching and learning experience?" he asked. "Or should we experiment and move forward?"[30] Given the far-reaching implications of predictive analytics on students' life outcomes, school leaders should avoid programs that use them.

## The economics of proprietary digital platforms and learning programs incentivize opacity and discourage adequate testing of their algorithms.

Raising questions about how a given piece of software actually works is a potential threat to its profitability.[31] An external audit of programming could, for example, flag serious problems that throw into question the ability of the software to do what its creators claim it can do. This could significantly delay, if not prevent altogether, schools from adopting it.

The proprietary nature of algorithms allows companies to conceal their programming. It also allows them to make stronger statements about the validity of the results they report than are necessarily warranted. Sara Marie Baker, former research director for a private healthcare consultancy, explained how this works: "The level of confidence with which you [as a business] can make statements or draw conclusions is greater because the data is proprietary and no one will see it. Your standards of scientific rigor are less. Even though the trendy term is 'predictive analytics,' it's not so much causality as a reliable correlation.[32] " This is an important warning for school leaders to consider when reviewing claims made about educational software. Digital platforms and learning programs that have undergone third-party algorithmic auditing—especially because of the economic incentives to avoid such review—are less likely to contain flaws that would negatively impact students.

## Digital platforms and learning programs may not adequately protect the student assessment data they gather and store.

In addition to whatever educational purpose they may serve, digital instruction and assesment by their nature function as mechanisms of behavioral record-keeping. Since assessment and other school-related data are extremely valuable, there are incentives to try to exploit any data not properly safeguarded. In one example with far-reaching implications, the state of New Mexico sued Google in 2020, accusing it of using personally identifiable student information it obtains from school-assigned Chromebooks and G-Suite for Education accounts to inform its advertising business.[33] In another example, an October 2019 breach of the Naviance college planning platform led to theft of 6,000 Montgomery County students' personal information, including their GPAs and SAT scores.[34]

Given the inadequacy of current safeguards, it is not surprising that threats to student data continue to increase,[35] despite voluntary guidelines supported by the tech industry,[36] legislation in some states,[37] and federal legislation in the form of the Children's Online Privacy Protection Rule (COPPA),[38] Protection of Pupil Rights Amendment (PPRA)[39] and the Family Educational Rights and Privacy Act of 1974 (FERPA).[40] FERPA, in particular, was weakened in 2008 and 2011 to allow schools to name technology companies as "school officials" and thereby to provide data to them without parental consent.[41] Contracts with companies serving as school officials may allow for them to share data with third parties, to send students to third parties without adequate data provisions, or to use student data for purposes outside their specified education purpose.[42] Rather than simply accept reassurances that a company collecting student data complies with technology industry self-regulation or relevant legislation, school and district leaders would be wise to carefully examine the contracts, terms of service, and privacy policies to which they are asked to agree in the name of their students. They should also ask specific questions about what the companies they contract with do with their students' data and how they protect it.

## Research Landscape Related to Digital Platforms and/or Learning Programs in a Virtual Environment: Assessment

**Michael K. Barbour, Touro University California**

In a review of the research on the nature and quality of the curriculum and student experience of virtual education, Barbour found "almost a complete absence" of research.[43] This is particularly true about the nature of assessment in virtual education. We therefore have to rely on limited and dated evidence, and on anecdotal reports. The existing evidence paints a picture of digital assessments that is less personalized than appears in marketing materials for virtual education.[44]

For example, in 2006, Klein found that the mastery-based curriculum used by the California Virtual Academy required students to achieve 80% on lesson assessments.[45] If they did not pass, they were returned to the lesson in order to retake the exam. She also found, at the time, that the student's "learning coach" (i.e., the parent/guardian) was responsible for determining if the student had successfully completed the outcomes of a specific lesson. Fourteen years later, features like these are built in to digital platforms' algorithms.[46] Ohanian found the same type of assessment in her 2004 evaluation of the K12 history curriculum for kindergarten through second grade:

Furthermore, the claim that lessons are adapted to the needs of each student is not borne out by the facts. If a student misses more than 20 percent of a lesson assessment, the parent is told the student must repeat the lesson. If the student again misses more than 20 percent, the instruction is to repeat the lesson again. And again. The so-called "needs of each student" is an endless loop of repetition of the same material.[47]

The same approach to assessment of content knowledge is described as part of the Summit Learning Program, a nationally marketed "personalized learning" program. Students take 10-item, computer-generated assessments on each section of content, which they repeat until they answer eight items correctly.[48]

The problematic nature of assessment in virtual education has been raised in the literature with both full-time and supplemental settings. For example, in a 2016 study of an online credit recovery program in North Carolina, Stallings and his colleagues found little difference in short-term success rates (as represented by, for example, end-of-course exam scores) between the online credit recovery students and other credit recovery students in the state.[49] When they examined graduation rates as a measure of longer-term success, they found that online credit recovery students were less likely to graduate than other credit recovery students. Those online students who did graduate were more likely to graduate within four years, however.[50] Further, Heppen and her colleagues' 2016 study of Algebra 1 credit recovery in Chicago Public Schools found students in an online credit recovery to report lower confidence in their mathematical skills than students in face-to-face credit recovery classes.[51]

The deficiency on long-term measures of success and the lack of confidence among online students suggests that the process of presenting small elements to students bit by bit may have helped some of them pass a mastery-based assessment immediately following the virtual instruction, but had little lasting impact on their knowledge or understanding of the overall curriculum.

## Conclusion

The adoption of commercial digital platforms and learning programs poses real risks to the integrity of student assessment. School and district leaders can minimize the risks by judiciously choosing and using products they bring into their schools. To minimize the risks, it is important that school educational programs properly frame consideration of any technology considered for adoption by ensuring that digital platforms and learning programs do not drive the curriculum, pedagogy, assessment, or data collection and record keeping practices of the schools. In order to properly determine whether and in what manner to adopt a digital platform or learning program, we recommend that school and district leaders consider:

- The pedagogical values, goals, and practices they hope to achieve before considering the adoption of a particular digital educational product;
- The ways in which any digital educational product would advance their self-defined values, goals, and practices;
- The potential negative consequences—in this case, for assessment—that may be associated with the use of that product and devise strategies for avoiding them;
- Which of their defined values, goals, and practices can be best achieved by non-digital means and which require digital means;

As they assess the suitability of any particular project, we recommend that they consider:

- The pedagogical theories built into the product's assessments;
- The ways that the product's assessments may shape and narrow the curriculum;
- Cultural and other biases that may be embedded in the algorithms that run the product's assessments;
- The dangers associated with predictive analytics, artificial intelligence, and machine learning;
- How the economics of digital platforms and learning programs may increase their opacity and discourage appropriate pre-implementation testing of them; and
- How the product gathers, stores, and protects student data created as a function of its assessments.

# Notes and References Section II


1 See, for example:

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Independent journalist Audrey Watters tracked venture capital funding for education technology from December 2015 through December 2018:

Watters, A. (2018, December). Who's Funding Education Technology? Hack Education. Retrieved July 10, 2020, from http://funding.hackeducation.com/archives.html

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Boninger, F., Molnar, A., & Saldaña, C. (2020). Big claims, little evidence, lots of money: The reality behind the Summit Learning Program and the push to adopt digital personalized learning platforms (Appendix A), Boulder, CO: National Education Policy Center. Retrieved July 9, 2020, from http://nepc.colorado.edu/publication/summit-2020

For discussion of Chan Zuckerberg Initiative and Gates Foundation support of personalized learning more generally, see:

Watters, A. (2017, July 18). 'Personalized learning' and the power of the Gates Foundation to shape education policy [blog post]. Hack Education. Retrieved July 10, 2020, from http://hackeducation.com/2017/07/18/personalization

For discussion of how the logic of personalized learning leads to a demand for assessment data, see:

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7 Compare to the description of teaching machines. Stephen Petrina (2004) explains the inherent contradiction embedded in the "teaching machines" of the 20th century: although they individualized students by providing them with individual feedback, they were also authoritarian and "normalizing": they regulated students by demanding that they discipline themselves within the structure imposed by the machine.

Petrina, S. (2004, April). Sidney Pressey and the automation of education, 1924-1934. Technology and Culture, 45(2), 305-330. Retrieved July 13, 2020, from https://www.researchgate.net/publication/236827543_Sidney_Pressey_and_the_Automation_of_Education_1924-1934

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14 Both Audrey Watters and Ben Williamson explore the ideologies, "imaginaries," and business interests that are embedded in education technologies. Their analyses inform our discussion of how education technologies frame education and influence students.

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See also:

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