Decoding Adaptive

Open Ideas at Pearson
Sharing independent insights on the big, unanswered questions in education

Pearson

EdSurge

About Open Ideas at Pearson

Pearson's goal is to help people make progress in their lives through learning. This means we're always learning too.

This series of publications, Open Ideas, is one of the ways in which we do this. We work with some of the best minds in education – from teachers and technologists, to researchers and big thinkers – to bring their independent ideas and insights to a wider audience.

How do we learn, and what keeps us motivated to do so? What is the body of knowledge and skills that learners need as we move into the second half of the 21st Century? How can smart digital technologies be best deployed to realize the goal of a more personalized education? How can we build education systems that provide high quality learning opportunities for all?

These questions are too important for the best ideas to stay only in the lecture theatre, on the bookshelf, or alone in one classroom. Instead they need to be found and supported, shared and debated, adopted and refined.

Our hope is that Open Ideas helps with this task, and that you will join the conversation.

About Pearson

Pearson is the world's learning company, with expertise in educational courseware and assessment, and a range of teaching and learning services powered by technology.

Our mission is to help people make progress through access to better learning. We believe that learning opens up opportunities, creating fulfilling careers and better lives.

About EdSurge

EdSurge was started in 2011 by Betsy Corcoran, Matt Bowman, Nick Punt, and Agustin Vilaseca to connect the emerging community of edtech entrepreneurs and educators. We wanted to share detailed information about what new technologies could – and could not – do to support learning.

We report on the latest news and trends in the edtech industry to help:

- Entrepreneurs who build new products and businesses;
- Educators who use these tools;
- Investors and others who support companies and schools.

In addition to reporting on trends, we share other information vital to all in the learning ecosystem, including available jobs, opportunities, and events. We are building a database of rich information (the EdSurge Edtech Index) about emerging products and how they're used. And we run a series of Edtech Summits where educators and entrepreneurs meet on common ground and exchange feedback on how to build and refine tools to improve educational outcomes.

We also do research that provides entrepreneurs and educators with information to make decisions, inform practice, and build bridges of communication between communities. We combine reporting, market intelligence, and a growing community of readers with independent research that is easy to consume and fits into the daily life of educators and entrepreneurs.

With the right tools, technology can transform "learning" from something we did in classrooms at fixed hours of the day to something we can do anywhere, anytime.

Acknowledgments

This report – in both its paper and online incarnations – reflects six months' worth of research, interviews, and reflection on the part of the EdSurge team, as well as many administrators and technologists in the field.

We are very thankful to the more than 30 administrators, technology directors, professors, and edtech executives who graciously shared their stories of adaptive learning with us. Their stories of frustration and triumph inspired and informed us continually through this journey. We'd also like to thank the entrepreneurs at companies we studied, who spent hours talking with us about the philosophical and practical underpinnings of their work.

A number of EdSurge staff put tremendous energy into creating this report. We are fortunate that many of them have been in the classroom themselves, or have administrative backgrounds. These include: Christina Quattrocchi, Peter Burrows, and Betsy Corcoran. Other teammates, including Brady Fukumoto and Patricia Gomes, helped to ensure that the associated microsite would support the framework we developed.

This work also couldn't have been possible without Pearson. Their financial support gave us the time and space to do this research. They were also tremendously generous with the time of their own internal experts, particularly Johann Larusson, Angie McAllister, and David Porcaro. We would also like to thank Sir Michael Barber, Amar Kumar, Laurie Forcier, Mark Griffiths, and Vikki Weston for their dedication to open ideas and to sharing meaningful research with the field.

The opinions, beliefs, and findings published on this website, and in the related report, were generated independently by EdSurge. EdSurge retains sole editorial control and responsibility for the content in this project.

We hope this work contributes to greater understanding of adaptive learning and are thankful to everyone who has helped to make it possible.

Kelly Blair
Researcher, EdSurge

Suggested reference: EdSurge (2016). Decoding Adaptive. London: Pearson.

ISBN 978-0-992-42501-2

Contents

Additional content associated with this report can be found at edsurge.com/research/special-reports/adaptive-learning

Foreword by Michael B. Horn

When Clay Christensen, Curtiss Johnson, and I published *Disrupting Class: How Disruptive Innovation Will Change How the World Learns* in 2008, we didn't use the phrase "adaptive learning" once in the book. Just eight years later, it's nearly impossible to imagine writing a book about educational technology and neglecting the term.

With the rapid growth of blended learning and technology more generally in schools, asking if educational software is capable of adapting to students' needs is commonplace.

Teachers are increasingly attempting to reach all of their students, each of whom have distinct learning needs, with the right learning experience at the right time. Having effective adaptive software turbocharges those efforts and can provide a realistic pathway to accomplish that goal.

But a critical challenge correctly noted in this report, written by EdSurge and supported by Pearson, is to decipher just what it means for a learning technology to be adaptive. A significant percentage of education software companies I talk to use the word adaptive almost nonchalantly to describe what they do. Meanwhile, CEOs of some education technology companies snicker that other products on the market aren't "really adaptive" despite their claims.

In many ways, the field of adaptive learning technology is in the same place now that K-12 blended learning was in 2010. Back then, leaders of schools implementing blended learning would bicker about which one was "really blended."

Unless clearly defined, the term "adaptive learning" – which connotes a powerful and important concept – risks becoming meaningless and useless to those who matter most: educators who must evaluate the claims software companies make to serve their students.

Having a definition is critical so that educators and technologists can have a common language through which to communicate about adaptive learning and its potential, not simply talking past each other. A sound underlying taxonomy of the different ways in which products are adaptive can enable educators to ask good questions to find the right software for their particular needs. And a common language will allow educators and technologists to discuss adaptive learning with greater depth, so they may build upon each other's ideas and improve the tools, not just talk about how to use existing tools.

To derive such a definition, it takes solid and sober research that is in touch with both the existing literature and the work in the field, so that it has credibility with stakeholders. It must avoid cheerleading – that is, it can't be normative to suggest that just because something is adaptive, it must be good. Some adaptive tools will be useful, whereas others will be misleading or unhelpful. Because of their vested interests, the individual companies are unlikely to be the ones to define it.

All of this is why EdSurge's work is so important.

This work represents the first serious and useful definition of what adaptive learning is alongside an accompanying taxonomy to describe how products differ from each other.

This taxonomy will also likely evolve, both as educators and technologists begin to use it to describe what is still a relatively nascent field and the field itself improves. But it offers a starting point to have these critical conversations — and ideally halt much of the miscommunication. And fortunately, because the process to create the definition and taxonomy was robust, it presents a way to continually improve it.

Adaptive learning is an enormously promising field. Educators worldwide are using adaptive tools to change their practice. The tools are growing and gaining acceptance in classrooms. I see adaptive tools in use almost every time I visit schools.

The tools, however, are not a panacea. For several reasons, it's unlikely that a single tool will ever be able to take over a student's education and direct them to every single thing they should do. Nor is it likely that we would want it to, as a critical part of education is building student agency – helping students own their learning, make decisions, become lifelong learners, and develop their metacognitive skills.

A critical part of education is also developing students' ability to interact and work with others – from the teachers who guide them and spark their interests and passions to their peers with whom they work, learn, and teach. Learning is ultimately a social experience, as it builds people into more mature social actors able to participate in civic society and lead productive lives.

But adaptive learning is a powerful force to make those pursuits more effective and efficient. Additionally, this technology can accelerate our knowledge of what learning experiences work best, for which students, in which circumstances, so that educators can adapt to a reality in which they can help all children find their passions and reach their fullest potential.

Introduction: Why we Need to "Decode Adaptive"

Over the past few years, EdSurge has dedicated itself to building bridges between edtech companies and educators through reporting, trend analysis, events, and product catalogues. Our mission to connect these groups in support of student learning has given us a unique vantage point from which to observe the advent of adaptive learning tools.

We've watched as the world fawned over the possibilities of adaptive learning technology, hoping that it would finally be "the thing" that would transform the classroom. We've reported on hundreds of millions of dollars being invested into these technologies – Knewton alone has raised nearly $160 million. And we've observed, with frustration, educators struggling to understand which adaptive learning technologies would be best for their students, as well as companies failing to communicate what practical value their technologies will add.

Despite the investments that have been made and the contracts that have been signed, there is very little consensus about what digital adaptive learning technologies are, what they can and cannot do, and how they work. We've had countless conversations with teachers who have identified a non-adaptive technology as their favorite "adaptive" tool. And our discussions with companies about whether their technologies are adaptive invariably feature the rejoinder, "Well yes, but what do you mean by adaptive?"

Watching educators and entrepreneurs struggle to communicate about this promising technology prompted us to ask three questions:

- What is adaptive learning?
- What's inside the adaptive learning black box?
- And how do the tools on the market differ?

The current effort is our attempt to answer these questions, contributing to a common understanding and definition of adaptive learning technologies. We believe this is critical, because the answers will help us move closer to making good on the promise behind this technology to improve teaching and learning.

Our research has led us to a definition, as well as a framework for understanding the different ways a tool might be adaptive. With this report we hope to provide educators with categories that map onto their instructional needs, so that they can better understand how a given tool will or won't help fulfill those needs. And with this information, it is our hope that educators will feel more empowered to advocate for the features they want in their classrooms.

Using our definitions and the framework, we have also categorized 24 popular and unique adaptive learning tools, based on their features, to provide exemplars of real tools in use today.

By providing a common language, we hope that edtech companies will be able to communicate their value more clearly, so that educators understand the impact each tool can have. Most importantly, we hope this research will move the field toward better decisions, better product design, better professional development for teachers, better implementations, and better outcomes for learners.

UNDERSTANDING THE ADAPTIVE LEARNING ECOSYSTEM

As you learn more about our definition and framework, we will also share a glimpse of the current adaptive learning ecosystem in the U.S., through stories of what this work looks like inside schools, classrooms, and companies. You'll find these vignettes interspersed throughout this report.

Defining Adaptive Learning

We began our work by interviewing a broad swathe of stakeholders – teachers, administrators, directors of technology, data scientists, and researchers – to understand how we could align the demand (educators) and supply (companies) sides of the market to foster clearer communication about adaptive learning technology. Our interviews revealed that, in the absence of a common definition, each had created his or her own (widely varying) definition of adaptive learning.

Some educators defined adaptive learning as an instructional strategy where a teacher alters his or her instruction in class to meet the needs of students. This could be as simple as changing the skill of the lesson or providing different resources for groups of students in class.

Others suggested that the term adaptive learning implied the usage of software. However, those who believe this differ in their definitions otherwise. There were disagreements about how automated the software should be before it can be considered adaptive. There were also disagreements about how complicated the underlying mathematics and data collection should be for a tool to be considered adaptive.

Adding layers of confusion, the term adaptive is often used interchangeably with other terms like differentiated, personalized, and individualized. These terms suffer the same fate as the term adaptive because there is a lack of agreement about what each one actually means. And, the term " adaptive learning" is often used in conjunction with terminology associated with advanced mathematics – for example, "algorithms" or "predictive analytics". The precise meanings of these terms and their relevance and application to student learning can be difficult to grasp.

Clearly, negotiating a common definition of adaptive learning is a necessary first step to having a productive conversation about it. The shades of meaning around what part of the learning process changes or adapts, what makes it change, and how often it changes has created a dense semantic forest filled with large, dark trees.

Based on our research, **we define digital adaptive learning tools as education technologies that can respond to a student's interactions in real-time by automatically providing the student with individual support.**

From this fairly simple definition, we can begin to parse out the subtleties that create a dividing line between what is and isn't a digital adaptive tool. Specifically, factors related to real-time data collection, automatic responses, and response or redirection for students based on their unique choices.

Adaptive learning tools collect specific information about individual students' behaviors by tracking how they answer questions. The tool then responds to each student by changing the learning experience to better suit that person's needs, based on their unique and specific behaviors and answers.

This differs to learning tools that provide the same responses for all students who click on a hint or simply answer a question incorrectly or correctly. Tools that mark an answer as correct or incorrect and then provide one singular path for learning, regardless of the student's response, are not adaptive. Tools that don't collect data in real-time are not adaptive. Tools that collect data through one singular assessment and prescribe a path of learning, but don't collect data or provide support in real-time, are not adaptive.

Our Methodology

We conducted this research and wrote this report to help clarify the types of adaptive learning technology that are currently available in schools and universities. Our goal was to help create a common language around adaptive learning by developing a set of definitions and a framework that educators can use.

To do this, we began with a review of the literature. We looked at over 20 articles written about adaptive learning, in order to determine the most important concepts and current themes.

Then, we conducted interviews with educators, product designers, and university professors to get their opinions on what the benefits and challenges are of adaptive learning. Of these 20 interviews; 15 focused on K-12 perspectives, 4 focused on higher education, and 1 focused on adult learning perspectives. Seventeen of the interviews were U.S. based, with one of each from South Africa, the United Kingdom, and Peru. Lastly, 10 of the interviewees work in public education, 2 of them conduct academic research, and 7 of them work in the field of education technology.

After completing our initial research, we studied 40 different, currently available, educational technology tools used across K-12 and higher education. We selected tools that use the word adaptivity or the term "adaptive learning" to describe how the tool works.

We also looked at tools that educators generally associate with these two terms. We did a deep dive into 24 unique but commonly used tools covering math, ELA, K-12, and higher education tools. This involved interviewing the users and creators of these tools to gain a deeper understanding of how each one worked on the back end.

As we developed our definitions and framework we conducted 20 additional interviews with educators and product designers, in order to solicit feedback and validate our approach. Our key findings are represented in this report.

Understanding the Adaptive Learning Ecosystem

Meet Aaron Cheng, a sixth-grade math teacher. He's a smart, technically savvy 28 year-old at the Alameda Community Learning Center (ACLC), a progressive charter school just fifteen minutes from the tech mecca of San Francisco. But when asked if ACLC is thinking of using any adaptive learning software, Cheng asks, "What's that?"

Thirty five miles south at Joseph Weller Elementary School in Milpitas, everyone knows about adaptive learning. Third graders sit on bright red plastic chairs in an expansive, airy learning lab, each quietly reading a book they selected from Reading Counts, an adaptive program that suggests titles to help them improve in a certain area – say, vocabulary. So many reporters and educators have visited this cutting-edge lab that teacher Diane Semrau doesn't bother to introduce the camera-laden visitors, and the kids could hardly care less. After they go off to lunch, district superintendent Cary Matsuoka and director of technology Chin Song sit for an interview, reeling off information about the program.

Of the two, Joseph Weller is simultaneously more – and less – like most schools throughout the U.S. As a traditional public school, it serves a staggering array of students with diverse needs. Forty percent are English language learners, compared to just 11 percent at ACLC, where students come from a more homogenous, upper-middle class community. Most Joseph Weller students, who between them speak ten different languages at home, live in cookie-cutter 1,100 square foot homes built by the Ford Motor Company early last century. Roughly 60 percent of the students perform at proficient or better levels, according to California standards, compared to 80 percent at ACLC.

"For us, the decision to use adaptive technology was about helping underachievers catch up," says Matsuoka. "And it was about helping kids take responsibility for their own learning. It's about student agency."

At schools like ACLC, where most of the students are doing just fine, there's a less pressing need for the technology – but plenty of nervousness about the problems it could create. When I describe the software to ACLC's Cheng, he stops to consider. "Well, I've only been teaching for three years, so I'd be willing to try. But I think a lot of teachers wouldn't want to change their ways." Pausing again, he adds, "And I'd want to see evidence that this stuff really works."

The need to change teaching practices. A perceived lack of evidence. Tight education budgets. Privacy concerns about software that creates a digital record of students' performance. Questions about the financial viability of some of the companies that make these tools.

These are the core challenges to adaptive technologies, arguably the most controversial and most tantalizing of the software to emerge in the past decade's pre-Cambrian explosion of education technology.

So far, adaptive technology, an education technology tool that can respond to a student's interactions in real-time by automatically providing the student with individual support, has touched only a fraction of America's K-12 students – maybe 20 percent, based on an informal poll of educators and entrepreneurs.

Yet it attracts attention because it takes aim at several fundamental questions: Can we create a way to deliver content that keeps students more engaged than the classic textbook? How much does the order in which concepts or skills are taught, or "sequenced", matter? How do we use testing – or assessment – not simply to rank students but as meaningful windows into why they struggle to learn? And the big one: Can changes in digital curriculum help close the aching achievement gap?

The need to tackle these issues cuts deeper daily: The students entering America's classrooms come from more diverse backgrounds and bring a wider set of needs and abilities than ever before in history. By contrast, funding for schools grows modestly at best. In most segments of life, when we've tried to do more with the same (or fewer) resources, we've invented tools to help.

But like so many bright and shiny technology promises, adaptive learning has yet to offer any definitive answers, despite decades of work. Both industry and teachers are wrestling with exactly what will constitute the "evidence" that so many educators crave.

If there's scant proof that these tools raise test scores, is it still worth doing if it makes students more enthusiastic learners, or if it frees up teachers to spend more time teaching to smaller groups? These questions unnerve many, including parents who don't want their children to get an inferior education as schools work out the kinks in new technology, and school district leaders, who are loath to champion risky projects that could get them in hot water with the school board, or on the front page of the local paper.

No one, even that most evangelical proponent of technological change, former Harvard Business School professor Clayton Christensen, promises change will be easy. New technologies, Christensen has observed, are typically inferior to existing ones – until people change the way they work. And so exploring what "adaptive learning" might mean in education has pulled a small group of educators, business, and philanthropists into a tentative and, at times, awkward dance. Here's what they are doing, and what they're learning along the way.

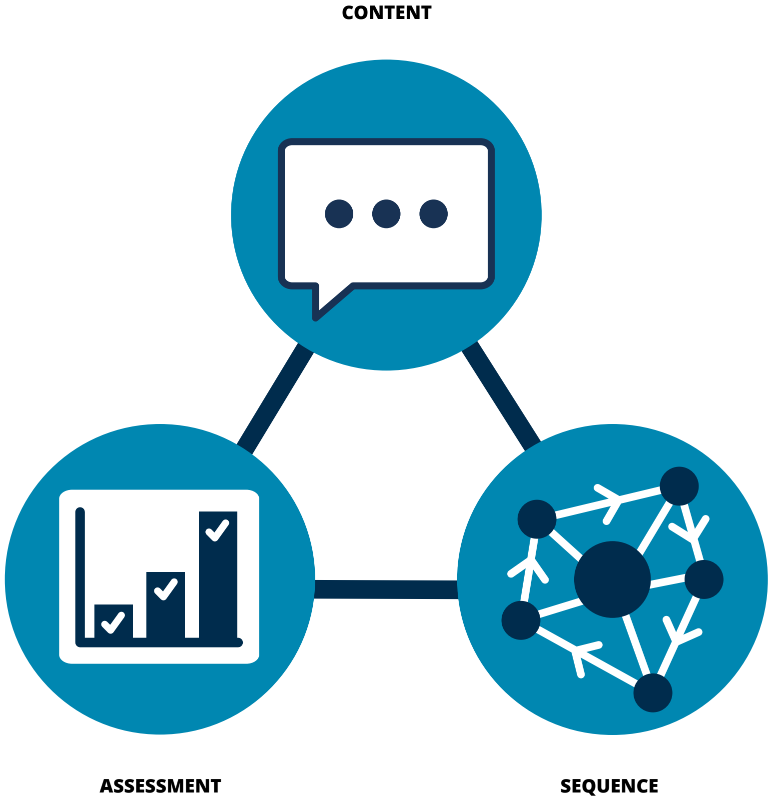
The story continues on page 32...

Navigating the Difference Between Adaptive Learning Tools

When looking for a digital adaptive learning tool, one of the hardest things to do is to figure out where a tool actually adapts. Often, the product information simply states the tool is "adaptive" or provides "adaptive learning," but adaptivity can be implemented in different ways. We did some research to understand how and when these tools actually change a student's learning experience.

What we found is that there are three places in a tool where adaptive learning normally occurs. They can have adaptive content, adaptive assessments, or adaptive sequences. It's common for tools to have adaptivity in more than one of these places.

Let's break these down a little further.



Adaptive Content

When a student makes an error, tools with adaptive content respond with feedback and hints based on the student's specific misunderstanding, providing additional materials for review. They also take individual skills and break them down into smaller pieces, depending on how a student responds, without changing the overall sequence of skills.

Tools with adaptive content are all about two things: looking at a student's specific answer, and then responding with unique hints, feedback, and resources on a specific topic. These responses to student learning are all applied within a single piece of content aligned to one skill, for instance, a learning activity on adding fractions.

These tools are able to respond to each student when he or she makes a mistake by providing corrective feedback (i.e. "you forgot to carry the remainder") and hints (i.e. "don't forget about place value"), based on the student's unique response. This feedback is more than simply marking answers as correct or incorrect.

What makes content adaptive?

There are many features that are essential to creating well-designed, effective content for students. Pedagogy and accuracy are very important but so are other things like student engagement and motivation. Content that is visually appealing or interactive, because it allows students to sort and match items or draw a diagram, is more likely to keep students engaged. In addition, content that offers students some control, by allowing them to choose their work or set their own pace, is more likely to lead to higher levels of motivation and achievement.

However, while interactivity, student choice, and self-paced environments are important to student outcomes, we do not consider them to be adaptive features within the content.

Adaptive features within content can respond to students' academic needs when they make a mistake by providing corrective feedback and hints, that are based on students' misunderstandings, as well as additional learning resources, and support for immediate remediation. This is different to simply telling students whether their answers are correct or incorrect after an activity or practice question. Adaptive content is able to respond to a student with targeted feedback, hints, additional learning resources, and scaffolded support.

Feedback & Hints
Some tools can provide corrective feedback aligned to a student's specific misunderstanding, so that the misunderstanding is corrected (e.g. Fulcrum Labs). Others provide suggestions or hints for how to answer a question based on a student's previous response (e.g. Mathspace, SmartBook).

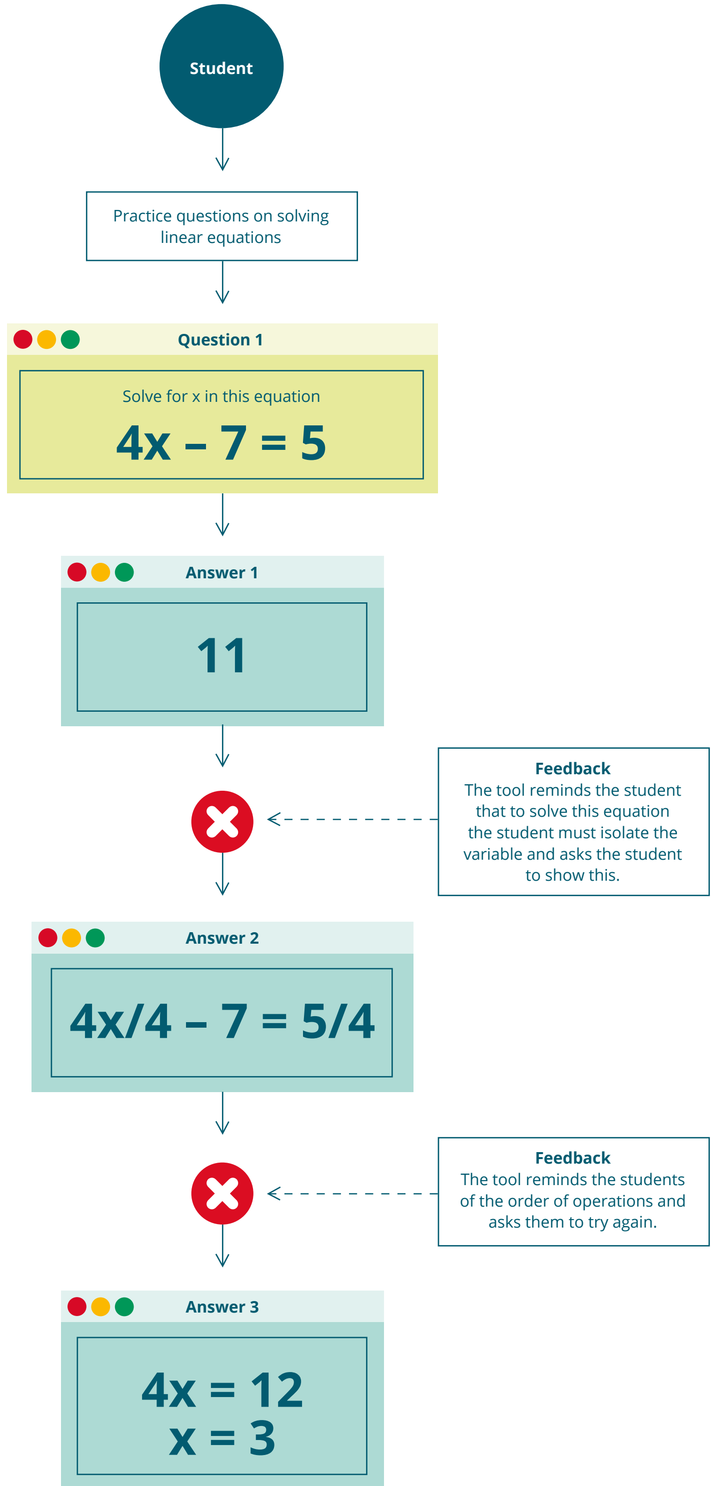
Additional Learning Resources
In addition to providing specific feedback and hints, some tools also offer additional learning resources – such as videos or texts – that students can use immediately to review a skill (e.g. Mastering, LearnBop). Moreover, some tools provide in-depth, step-by-step remedial instruction that students can access as needed (e.g. KnowRe), while others allow students to reach out to a tutor from within an activity to request additional tutoring (e.g. Think Through Math, MyLab).

Content Scaffolding or Branching
The most complex feature of adaptive content is scaffolding or branching. This feature is most analogous to a teacher working with an individual student on a single skill or concept while scaffolding the practice by breaking it down into parts until the student can put the parts back together, and demonstrate the original skill.

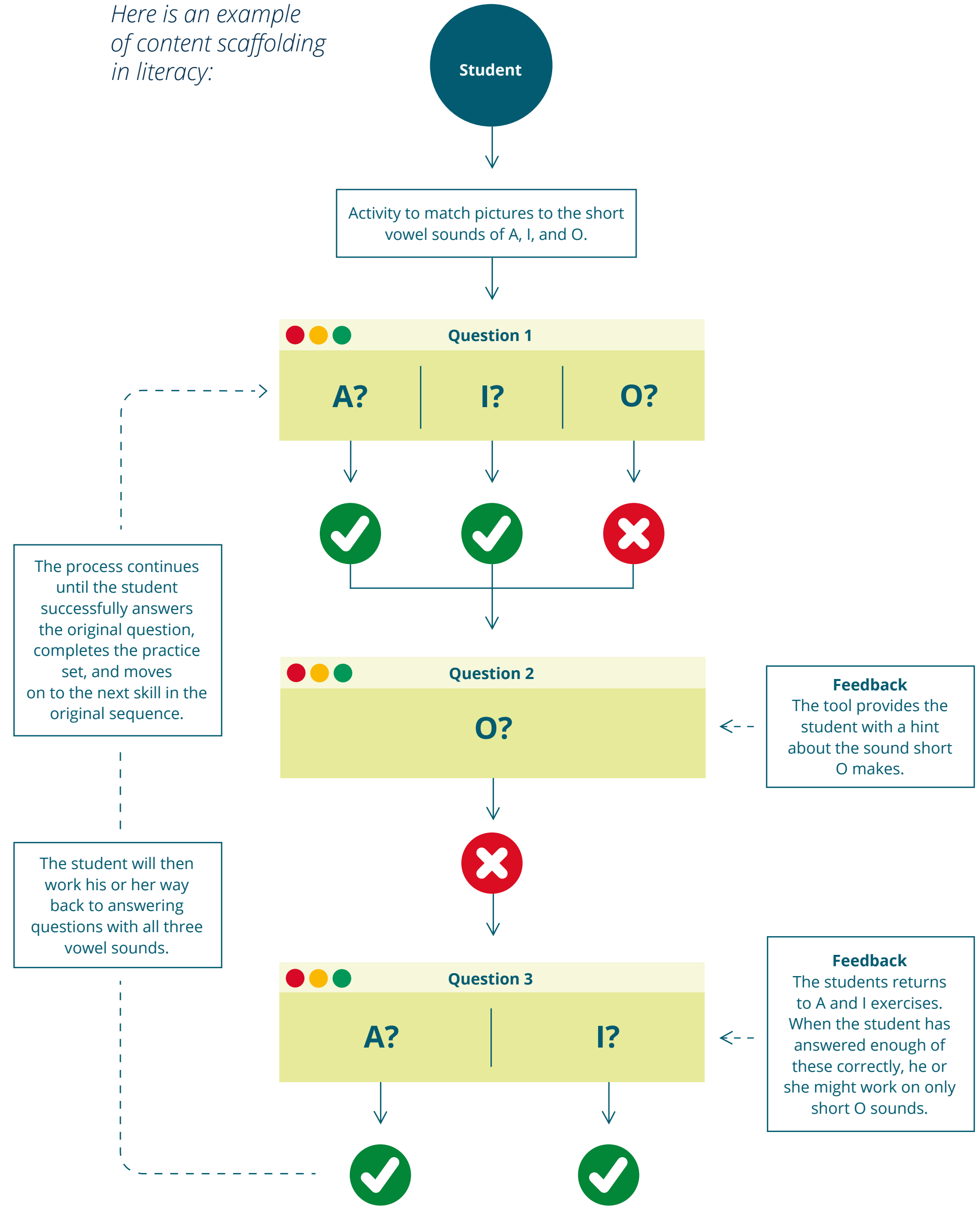
There are two key elements of content scaffolding or branching: the adaptivity is contained within one unit of content that's aligned to one skill, and the student's original sequence of skills remains the same.

When this happens, the student will continue to work on the same skill until he or she masters it and can move on, or until a teacher is notified on his or her dashboard about the need for additional help and intervenes. When a student has demonstrated mastery of that one skill he or she is moved on to the next skill in the original sequence. The information collected about the student's performance on the skill is not used to redirect the student to an entirely different skill. The student's original sequence remains the same.

Here is an example of content scaffolding in math:



Here is an example of content scaffolding in literacy:



Tools with content scaffolding usually collect data on how a student performs within the individual piece of content, and then displays the data on a dashboard for teachers to see and use.

Adaptive Assessment

The key to understanding adaptive assessment is to remember that these tools change the questions a student sees, based on his or her response to the previous question. The difficulty of questions will increase as a student answers them accurately. If the student struggles, the questions will get easier.

This category of adaptivity is focused entirely on a tool's assessment features or capabilities. Adaptive assessments change and respond based on whether students answer questions correctly or incorrectly. This change is often a result of the difficulty level of the question.

For example, if a student answers an easy question correctly, the next question provided will offer increased difficulty, and so on.

What makes assessment adaptive?
Traditionally, assessments are designed in two ways: fixed-form or adaptive. A fixed-form assessment is one in which the items are preselected, and every student is tested on the same set of questions (e.g. a final exam). In an adaptive assessment, the items change based on how individual students answer each question. This change is often a result of the difficulty level of the item. For example, if a student answers an easy question correctly, the next item they receive will be a little harder, and so on.

Of the tools we studied, we found that there were two ways that adaptive assessments were used: as a practice engine; or as a benchmark assessment for monitoring students' progress.

Practice Engine
An adaptive assessment that is used as a practice engine consists of a pool of questions at different difficulty levels, which are aligned to the content a student has just reviewed. These assessments usually come after lessons, and students answer the questions to demonstrate mastery of the skills. For example, a tool might have a group of content for a student to study, and then an adaptive practice engine to prove what he or she has learned.

The student continues to tackle questions in the practice engine until he or she has answered enough of the difficult questions correctly. Once the student has achieved the mastery goal, he or she moves on to the next skill in the sequence (e.g. Fulcrum Labs, LearnSmart).

Benchmark Assessment
An adaptive assessment that's used as a benchmarking tool is usually a longer, more formal test that is administered every few months in order to measure how much students are learning. These assessments are usually given as stand-alone tests.

For example, students might take an online adaptive assessment every three or four months to measure what they've learned. The results are usually communicated through a data dashboard and reports (e.g. i-Ready Diagnostic, Lexia Rapid, NWEA). In addition, some tools analyze the results and create a learning path for each student to work on until the next adaptive assessment is administered by an educator (e.g. i-Ready Diagnostic).

Since some of these assessments are used to measure academic progress, extra steps are taken to make sure that they are high quality tests. Mathematical models are used to analyze how large groups of students perform on different parts of the test, to insure that the items are reliable and valid.

Adaptive Sequence

Tools with adaptive sequences have a lot going on behind the scenes.

These tools are continuously collecting and analyzing student data to automatically change what a student sees next; from the order of skills a student works on, to the type of content a student receives.

Tools with adaptive sequences are the most complex of the three. They often make use of algorithms and predictive analytics that can continuously collect data and use it to change what a student sees.

What makes a sequence adaptive?
A tool with adaptive sequencing differs from a tool that simply provides differentiated content for students. Those tools might not be collecting real-time data and using that data to change the sequence of what a student learns next.

For example, DreamBox assigns individual students a group of math content to work on. As the student interacts with the content, either by answering questions, clicking on hints, or using virtual manipulatives, DreamBox saves this information about the student's actions. When they complete the assignment, the tool analyzes the student's academic performance and learning behaviors, before mataching them to a new set of skills based on his or her performance. Then, DreamBox automatically assigns the student a new group of content.

These tools differ to ones which simply provide differentiated content for students. For instance, there are a group of tools that provide an assessment, analyze the assessment data, and then assign a learning path for each student based on their assessment results. Students work on these learning paths until another assessment is manually administered, and a new learning path is created (e.g i-Ready, Lexia).

While these types of tools differentiate content for students, they do not have a truly adaptive sequence. They do not continuously collect data on a student's performance within the content or assessments, and use the data to automatically adjust a student's learning path.
Adaptive sequencing is the ability to continuously collect real-time data on performance and *use it* to automatically change a student's learning experience.

What we found is that tools with adaptive sequences engage in a three step process. First, the tool *collects* data. Then, it *analyzes* the data. Finally, the tool *adjusts* the content a student will receive next.

The process

Here's a simplified example of the adaptive sequence process: Several students are assigned different math content to work on. As each student interacts with the content, either by answering questions, clicking on hints, or using virtual manipulatives, the tool saves information about each student's actions. When a student completes the assignment, the tool analyzes their academic performance and learning behaviors and then matches the student to a new set of skills based on performance. The platform automatically assigns the student new content.

This is different to simply providing differentiated content for students. For instance, if a learner was not in class during a period when a particular skill was introduced, and years later was learning a new skill that built on that prior knowledge, that learner would struggle. Adaptive sequencing tools could help that student go back to find this gap and learn this content first, rather than following the same sequence as everyone else.

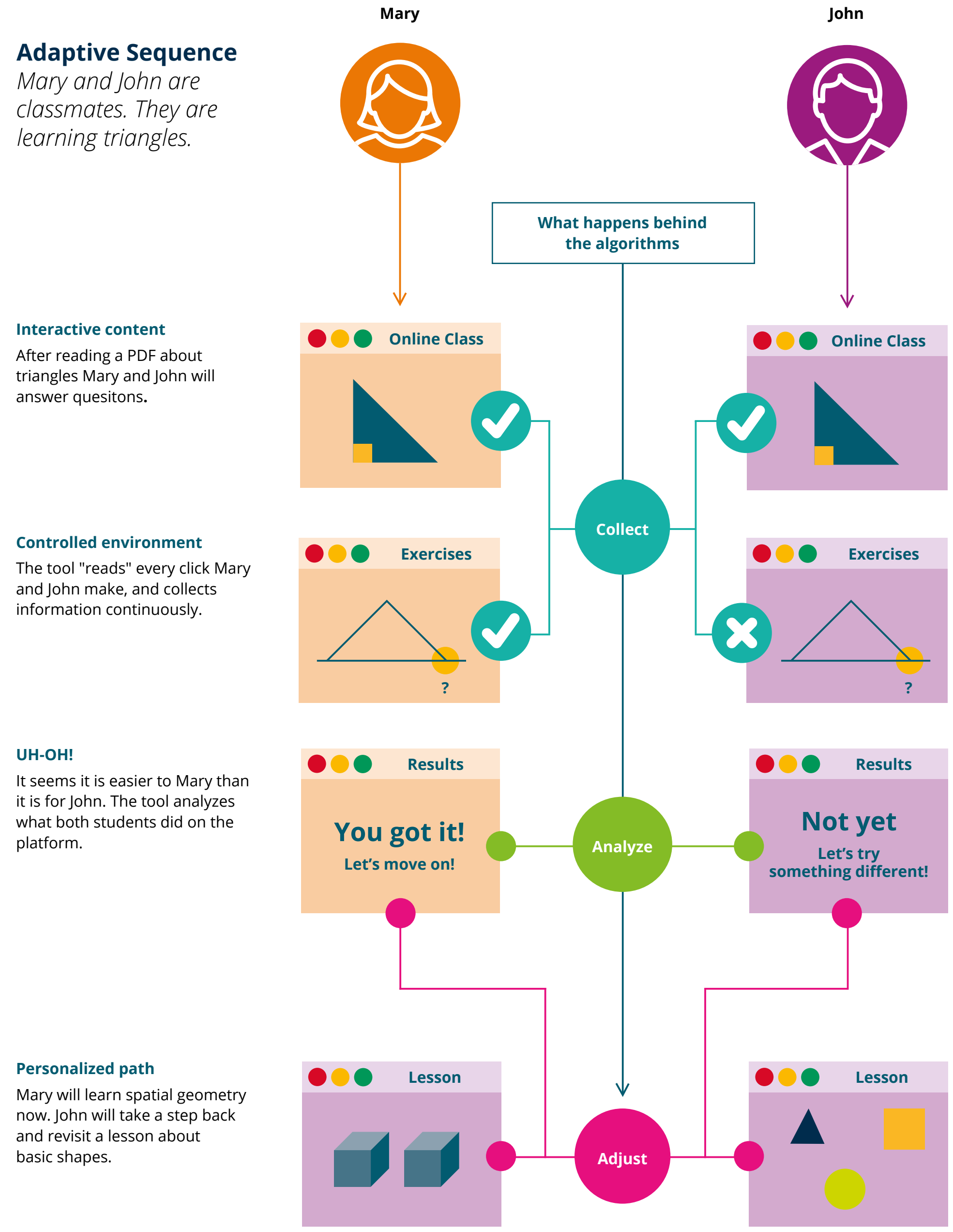
Tools that provide assessments, analyze the assessment data, and then assign a learning path but don't change the learning path until another assessment is administered, are not adapting the sequence of the learning materials.

Some tools use a slightly different version of adaptive sequencing to recommend additional resources for students, based on their needs. These tools collect and analyze student data, before adjusting content by recommending optional materials, which the students can then use to help with their existing assignments. They aren't as prescriptive as other tools in this category.

Some tools adapt in multiple ways

In addition to identifying these three areas of adaptivity, we found that the tools we studied have adaptive features in one or two of these areas. For example, Lexia Learning has adaptive features within the content that enable the tool to immediately respond to students' mistakes, using corrective feedback and scaffolded practice. While Lexia does have assessments, the assessments are not designed to be adaptive and the sequence of content is set for students after they take an initial placement test. Lexia Learning has adaptive features only within the content.

However, a tool like KnowRe has adaptive features within the content and within the sequence. The content in this mobile app can provide step-by-step instructions and additional videos to help students solve math problems they are struggling with. In addition, KnowRe also collects data on how individual students perform over time, and uses it to provide students with practice questions aligned solely to the skills that they need. Therefore, adaptive features are located in both the content they review and the sequence of skills a student works on.



Of the different categories of adaptivity, tools with adaptive sequence are the most complicated to understand. Because decisions around the sequence of instruction are important to teachers, we wanted to dissect how these instructional decisions were made by tools. After thorough exploration of 24 different tools, we decided to take a closer look at how changing the sequence of content actually happens.

Changing Practices

Some of the most widespread education technologies did not demand much change in teachers' practices. Digitized books were, after all, just books in a different medium. PCs and Chromebooks provided an electronic replacement for typewriters and paper and pencil, but didn't immediately revolutionize the classroom.

Adaptive learning does not fit easily into the status quo. Besides having to use a blended learning model, in which class-time is divvied up between traditional and electronic learning, teachers must be willing to let students progress at their own pace. They need to be comfortable letting software make real decisions about what students should learn next, and use quantitative data on student performance gathered by the software along with their own qualitative gut instincts. They need to be willing to trade the stand-in-the-front-of-the-room-and-lecture model, and instead provide more intimate, personalized instruction to whichever students aren't on computers at that given moment.

At Aspire ERES Academy in Oakland, CA, students spend up to a quarter of their day (50 to 80 minutes in total) using online tools, including ST Math and i-Ready. Like the Milpitas public schools, Aspire Public Schools, which operates 38 schools in California and Tennessee, saw adaptive technology as the most efficient way to achieve its goal of college-readiness for students in low-income populations. At ERES Academy, 99 percent of the students re English learners.

Besides the obvious logistical challenges of a blended classroom, such as setting up rotations for students to cycle from teacher time to computer time, using adaptive learning tools requires other changes. Every Friday, second-grade teacher Mark Montero has 15 to 30 minute "data talks," when the students talk about their progress and the problems they ran into using the adaptive products. Students who are doing particularly well are named "student coaches". Montero makes a list of who is struggling with what, and assigns one of the coaches to spend the last 10 minutes of their 30 minute rotation helping one of their classmates overcome the hurdle. "Kids need to discuss what they're doing on the computer," he says.

Adaptive technology requires a different sort of trust between teacher and student. "You have to let go of some of the micromanagement," says Montero.

"You have to trust that each student is working hard, and working at their top level," rather than idly clicking. To keep them honest, there's a drawing of a traffic light in front of every student's Chromebook.

If Montero thinks a student is slacking off, he shines a laser pointer at the yellow light. If he has to come back and shine it on the red light, the child has to get off the computer. The "Are You Still There" screen saver in i-Ready that pops up after a few inactive minutes is also a mark of shame for a student. And of course, Montero can always check the extensive data stored by these tools, including how many lessons students have passed and how much time they put in.

At the same time, teachers can't get too enamored with the technology. When Weller Elementary first rolled out i-Ready, "we made the mistake of thinking data was the holy grail" says superintendent Matsuoka. At first, the plan called for teachers to stay in the classroom while their students went to the learning lab. This would work because the data generated by the adaptive tools would inform the teacher's lesson plans. "Let's just say that was a bad assumption", Matsuoka says. He won't share details, but admits the district learned the hard way that results don't improve when teachers spend too much of their lesson-planning time mining data. "Data is important, but it's not the most important thing. The most important thing is quality teaching", he notes.

And quality learning. While there isn't definitive proof of a link between adaptive learning and better mastery, Matsuoka says he has no doubt it has helped close the achievement gap for many struggling students.
It's certainly helped with behavior: the number of suspensions at Weller fell from 50 to zero in the year adaptive learning technology was rolled out.
Just as gratifying, Matsuoka says, is watching gifted students race ahead, unshackled for the first time in their school careers.

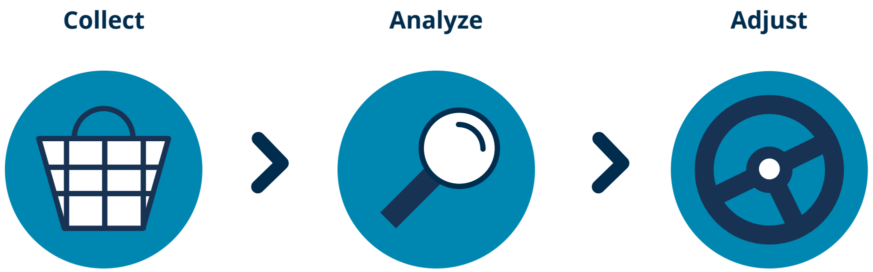
"Some kids go slower and some kids go faster," says nine-year-old Arielle Talucod, a calm, confident students who was tapped to give demos of the various programs she uses.
She's clearly in the faster group. While many of the children use points won for the number of books they read to unlock little video games, she evidently doesn't have time to waste. "I'm saving up," says Arielle, who is clearly a long-term planner. She hasn't decided yet whether to be an astronaut, or President of the United States.

The story continues on page 48...

What's Behind Adaptive Sequence: How are Instructional Decisions Made by Adaptive Learning Tools?

Three Simple Steps to Changing Sequence: Collect, Analyze, Adjust

Adaptive sequence tools engage in a three step process. First, the tool collects data. Then, it analyzes the data. Finally, the tool adjusts the content a student will receive next.



Collect

The first step in the process of changing a sequence is collecting data. There are three key characteristics of the data that are collected: the type of data, the difficulty level and item granularity, and the learner's history.

Type	Granularity + Difficulty	History
What type of data is collected and used?	What levels of knowledge are captured?	Does the tool consider a learner's previous performance?

Types of Data

Tools can collect and use different types of data based on how the student interacts with the content. The most common types of data used to change a sequence include:

- Academic performance: e.g., the answer a student submits for a math problem.
- Learning process: e.g., the number of times a student attempts a question before getting it correct, or the types of resources that a student uses for help - such as a virtual calculator or timeline.
- Student interest: e.g., the types of resources a student repeatedly chooses to interact with.

Other data can be collected, such as social behaviors (e.g. posting a comment on another student's feed), ratings (e.g. whether you like an activity or not), or even mood (e.g. identifying how you're feeling that day). However, these data are less commonly used in current technology to change a sequence of content.

Difficulty Level and Item Granularity

Difficulty level and granularity represent two related things. Difficulty levels refers to the complexity of the problem the student worked on. There are different scales that can be used for this, such as Webb's Depth of Knowledge, Bloom's Taxonomy, or simply: easy, medium, and hard.

Granularity means the level of detail at which a concept or skill is captured. The most common categories of data include:

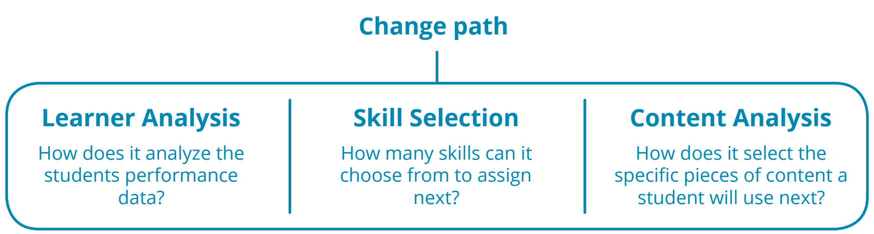
- The general standard or topic.
- The specific concept.
- The discrete knowledge or skill.
- The cognitive difficulty level.

Learner History

Learner history represents a tool's ability to use data from a student's prior performance. If the tool does remember how the student has previously interacted with the content, then this information is added to the data pool and considered during the process of changing a student's path. Over time, the tool creates a profile of the learner's interactions with the content, which continues to grow as the student uses it.

Analyze

After collecting this type of information, the tool analyzes it to establish what skills the student knows and doesn't know. Tools do this by analyzing performance, selecting the appropriate skills for each student, and selecting specific pieces of content that would work best for them.



Learner Analysis

The learner analysis process can be as basic as using a pass/fail score like 70%, whereby a student who scores above this range moves on to the next skill in the sequence, and a student who scores below it goes back to the prerequisite skill. This is often referred to as "gating" or "threshold scores".

It can also be a little more complicated when score weighting is involved. This is similar to the way in which educators often determine final course grades for students. Professors base these grades on a combination of factors and values, such as 10% participation, 20% homework, 30% final exam, and 40% group project. Digital adaptive learning tools can do this too, and then take the student's score and match it with the next best skill in the subject's overall scope and sequence.

Sometimes an adaptive learning tool doesn't just rely on a prebuilt scope and sequence to determine what the next best skill is for a student. Sometimes, it relies on other students and how they have performed. These tools are able to estimate what a student does and doesn't know by comparing similar students' profiles. The basic idea is that if it worked for one student, it will most likely work for another (with a lot of math behind it). Here's how it all breaks down.

Learner analysis is the process through which the tool analyzes the student's performance data. This is often where algorithms enter the picture. More than one mathematical measure is often used, the most common methods being:

- Weighting categories of data: weight the number of times a student submitted the correct answer as a higher priority than how much time the student spent on a set of questions.
- Applying thresholds of mastery: apply a rule such as 80% mastery to determine when a student has met expectations.
- Comparing groups of students data: compare one student's learning profile to another similar student's profile.
- Calculating probability of mastery: calculates how likely it is that a student has mastered a skill.
- Applying rules for correct and incorrect responses: send students to the activity that's already aligned to the correct or the incorrect response.

Skill Selection

When matching a student to the next skill on his or her path, there are a few different approaches. The tool can either have one skill to select from, a few skills to select from, or an infinite number of skills to select from.

Tools that have only one option move students to the one skill that was previously aligned to a response. For example, if a student incorrectly selects answer B on a multiple choice question about using decimals in math, the tool will send the student to the remedial skill previously aligned with answer B, such as determining place value. However, if the student correctly selects answer A, the tool will send the student to the next skill in the sequence that was previously aligned with answer A, such as multiplying decimals. These types of tools rely heavily on a predesigned scope and sequence, or content map that outlines what the connections are between each unit of content.

Tools with a number of options have the ability to allow students to return to skills that were taught in previous units, or skills that were taught in previous grade levels. These types of tools rely on predetermined scopes and sequences that are sophisticated enough to allow for this level of flexibility.

Lastly, tools that have infinite options allow students to go to any skill that other students with similar profiles previously worked on successfully. Tools like this primarily use large sets of actual data on student performance rather than a predetermined scope and sequence to match a student with a skill. Because of this, these tools generally create the most dynamic learning paths for students over time.

Adjust
After the tool has collected and analyzed the information, it adjusts how content is delivered and how much content is provided for a student. Most tools do this automatically and provide students with new required assignments or new optional supporting resources.

Match

Delivery	Amount	Design
How is the content delivered?	How much content is provided?	Is there a relationship between the content?

Delivery
Delivery represents the way in which new content is provided to students. In general, there are two ways this can happen: content is assigned or content is recommended. When content is assigned, students are required to complete it. For example, a student might receive a new assignment to work on that includes five different activities on subtraction.

In some cases, additional content is recommended for students. When this happens, students can choose whether to use these suggested resources. For instance, a student working on an economics assignment might also have a list of suggested resources that include a video describing the principles of supply and demand, as well as a written case study illustrating the relationship between supply and demand in context. In both scenarios, the additional content a student receives is tailored to his or her needs.

Amount
Amount indicates the size of the content assignment or recommendation. It is either an individual piece of content or a group of content. For example, a tool might assign an individual practice question for a student to work on next, or it might assign a group of 10 activities for a student to work on next.

Design
Design represents the relationship between the content in the assignment or recommendation. The content can be related or independent. Content that is related is often based on a similar unit and has a sequence. For instance, a group of related content could be ordered activities that are all aligned to measuring volume. Conversely, content that is independent is not connected at all and may appear in a resource bank, or as a general playlist. For example, a group of independent content could be a collection of individual math problems or resources that other students have liked and used.

Dissecting Adaptive Sequence Tools

As we studied the details of adaptive sequence tools, we began to see patterns in how tools collected data, analyzed it, and adjusted the sequence. To illustrate those patterns, we've shared some common profiles for these tools below.

Example 1: The All-In-One Tool
This first example is called "The All-In-One Tool" because it most closely represents how teachers currently change content for students in K-12 classrooms.

Like a teacher, these tools collect information about the academic skills that students are mastering, as well as the processes that students are going through to learn these new skills. Next, the tool analyzes the data using some cut scores and weighting determing what skill a student should work on next from the subject's overall scope and sequence. Finally, the tool adjusts the student's content by assigning them a new group of activities based on these skills.

Here's how they cover the different phases of the adaptive sequence process:

- Collect
  - **Type:** academic performance data, learning process data
  - **Granularity + Difficulty:** discrete skill, specific concept, difficulty level
  - **History:** learner's profile over time
- Analyze
  - **Learner Analysis:** weighting categories, applying thresholds of mastery
  - **Skill Selection:** few options
  - **Content Analysis:** not used
- Adjust
  - **Delivery:** assigns content
  - **Amount:** group of content
  - **Design:** related content

Product Examples: DreamBox, Mathspace

Example 2: The Comparison
The next type of tool, "The Comparison", can compare similar students' performance in order to determine what might work best for a student by using real data.

These tools collect information about the academic skills that students are mastering as well as the processes that students are going through to learn these new skills. Next, the tool analyzes the student's performance and compares their profile to other similar students' profiles, behind the scenes, in order to estimate what the student most likely does and doesn't know. Then, it selects a skill for the student based on the skills that the similar students previously needed and used. Finally, the tool adjusts the student's content by assigning them a new activity.

Here's how they cover the different phases of the adaptive sequence process:

- Collect
  - **Type:** academic performance data, learning process data
  - **Granularity + Difficulty:** specific concept, difficulty level
  - **History:** learner's profile over time
- Analyze
  - **Learner Analysis:** comparing groups of learners' data
  - **Skill Selection:** infinite options
  - **Content Analysis:** not used
- Adjust
  - **Delivery:** assigns content
  - **Amount:** individual content
  - **Design:** independent content

Product Examples: Knewton, Waggle, CogBooks, SuccessMaker

Example 3: The Recommendation
Some tools use an adaptive sequence to provide supporting materials for students, which complement a teacher's in-class assignments. In these tools, additional resources are aligned to student's academic needs and recommended for students to use. Unlike an assignment, the content is recommended, but not mandatory to move forward.

For example, these tools collect information about the academic skills that students are mastering, as well as the processes that students are going through in order to learn them. They also collect data on how students use materials in the tool, and whether they find certain content to be interesting or helpful.

Then, the tool analyzes the data by comparing the student's profile to other students' profiles to establish what content similar students used that was interesting or helpful. Finally, the tool adjusts the student's content by recommending several supporting activities that similar students found to be useful.

Here's how they cover the different phases of the adaptive sequence process:

- Collect
  - **Type:** academic performance data, learning process data, interest data
  - **Granularity + Difficulty:** general standard or topic
  - **History:** learner's profile over time
- Analyze
  - **Learner Analysis:** comparing groups of learners' data
  - **Skill Selection:** not used
  - **Content Analysis:** usage, interest, effectiveness
- Adjust
  - **Delivery:** recommends content
  - **Amount:** group of content
  - **Design:** independent content

Product Examples: Fishtree, Brightspace LeaP, MyLabs

Example 4: The Do-It-Yourself (DIY)

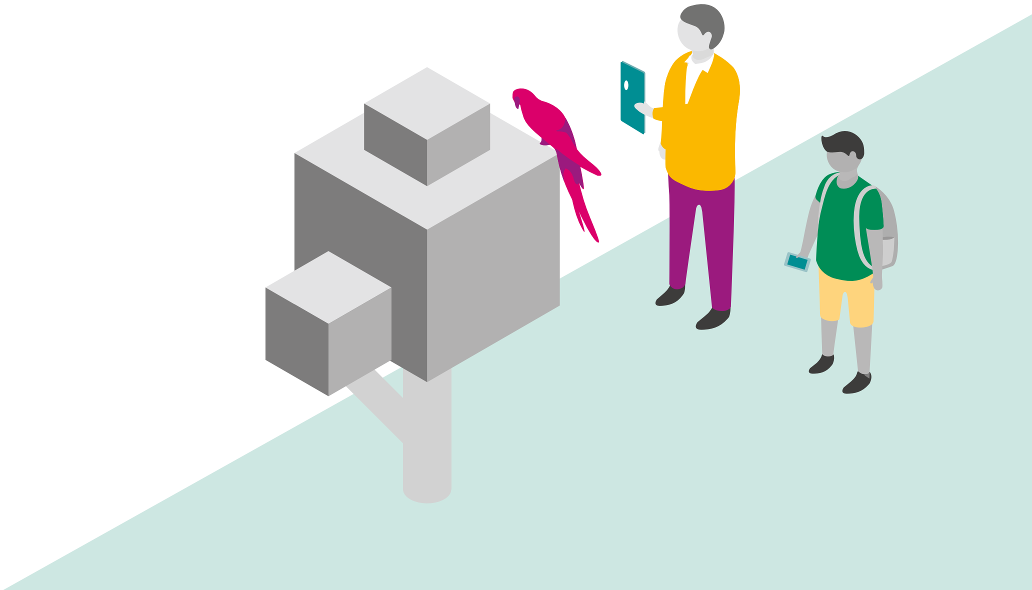
The last example is "The Do-It-Yourself" or "DIY". Some tools allow teachers to create their own courses from scratch. When using an authoring platform like this, it is possible to create pathways where students experience unique learning sequences aligned to different skills.

The process of changing the sequence is pretty simple. After a student reviews a piece of content, he or she answers a question related to it. The tool collects this information and analyzes whether the student got the answer correct or incorrect. Then, it adjusts the student's sequence of content by assigning them a specific activity, as predetermined by the teacher for each response.

Here's how they cover the different phases of the adaptive sequence process:

- Collect
  - **Type:** academic performance data
  - **Granularity + Difficulty:** determined by the author
  - **History:** not used
- Analyze
  - **Learner Analysis:** correct or incorrect response
  - **Skill Selection:** one option
  - **Content Analysis:** not used
- Adjust
  - **Delivery:** assigns content
  - **Amount:** determined by the author
  - **Design:** determined by the author

Product Example: Smart Sparrow



Tool Breakdown: Zooming in on 24 Tools

The edtech market is flooded by tools that offer, or claim to offer, adaptive learning features. On the next page, you can compare and contrast features of 24 different tools analyzed through the course of our research. Who offers adaptive content or adaptive assessment? Which tools use adaptive sequence? And which ones employ all three approaches?

We've got answers.

Importantly, our list is by no means exhaustive. It's a representation of well-known tools, new tools and tools that have unique characteristics in both the K-12 and higher education markets. You'll also notice a mix of tools including math and literacy tools, as well as authoring platforms and Learning Management Systems. But there are plenty more tools available than those we analyzed. So, take our framework as a starting point to ask questions about additional tools, and you can decide where the others should fit.

Additional information on all the tools studied can be found at edsurge.com/research/special-reports/adaptive-learning/software

Where it Adapts	Tool	URL	Description
Assessment	Ck-12 Platform	edsurge.com/product-reviews/ck-12-platform	Provider of open-source STEM content; allows teachers to compile and share custom digital textbooks.
Assessment, Sequence	Aleks	edsurge.com/product-reviews/aleks	Math assessment and tutoring system for K-12 and higher education..
	Learnsmart + Smartbook	edsurge.com/product-reviews/mcgraw-hill-learnsmart	Adaptive technology that supports over 1,300 McGraw-Hill courses.
	ScootPad	edsurge.com/product-reviews/scootpad	Adaptive platform for K-5 students to practice math and reading skills.
	SuccessMaker	edsurge.com/product-reviews/successmaker	Reading and math software for grades K-8, providing individualized learning paths.
Content	LearnBop	edsurge.com/product-reviews/learnbop	Automated online math tutoring and analytics tool for 5th-9th grade students.
	Lexia	edsurge.com/product-reviews/lexia-reading-core5	Reading software for foundational skills in preschool and elementary grades.
	St Math	edsurge.com/product-reviews/st-math	Visual and conceptual math program based on neuroscience research from UC Irvine, for grades PreK-12.
Content, Assessment	Fulcrum Labs (Formerly Adapt Courseware) St Math	edsurge.com/product-reviews/adapt-courseware	Comprehensive higher education curriculum with videos, texts, interactive practice, and quizzes.
	i-Ready	edsurge.com/product-reviews/i-ready	Adaptive assessment and instruction for math and reading in grades K-8.
	Istation	edsurge.com/product-reviews/st-math	Visual and conceptual math program based on neuroscience research from UC Irvine, for grades PreK-12.
	Mastering	edsurge.com/product-reviews/mastering	A higher education tool that provides content, tools, and experiences for students in science and engineering.
	Think Through Math	edsurge.com/product-reviews/think-through-math	Adaptive math program providing adaptive instruction, motivation, and live support.

Where it Adapts	Tool	URL	Description
Content, Sequence	CogBooks	edsurge.com/organizations/cogbooks	Helps educators deliver personalized learning for students.
	Dreambox	edsurge.com/product-reviews/dreambox-learning	K-8 math games product that adapts to the learner's level of knowledge.
	Knowre	edsurge.com/product-reviews/knowre	Math program that assesses strengths and weaknesses and provides content to fill gaps.
	Mathspace	edsurge.com/product-reviews/mathspace-product	Mathspace tracks and provides feedback on all aspects of a math problem, including intermediate steps.
	MyLab	edsurge.com/product-reviews/mylab	A higher education tool that provides immersive content, tutorials, and study plans for over 80 different courses.
	Redbird Advanced Learning	edsurge.com/product-reviews/redbird-advanced-learning-courses	Adaptive K-12 digital curriculum, blended learning services, and professional development.
	Smart Sparrow	edsurge.com/product-reviews/smart-sparrow	Adaptive eLearning platform to create and deploy rich, interactive quizzes and simulations.
	Waggle	edsurge.com/product-reviews/waggle	Offers Common-Core aligned instruction and assessment for math and English students in grades 2-8.
Sequence	Brightspace Leap	edsurge.com/product-reviews/desire2learn-product	Provider of digital enterprise solutions and learning management systems.
	Fishtree	edsurge.com/product-reviews/fishtree	Adaptive learning platform that curates, aligns, and personalizes online courses.
	Knewton	edsurge.com/product-reviews/knewton	Adaptive learning platform that customizes educational content based on student needs.

Can Districts Adapt?

Adaptive learning also requires major changes from the districts and school administrators that want to go down that path. One of the largest deployments currently underway is in Baltimore County Public Schools (BCPS), which began rolling out adaptive tools including DreamBox and i-Ready last autumn, after four years of exhaustive planning.

With 175 schools and 111,000 students, the BCPS team spent 18 months doing hundreds of interviews with teachers, parents, local businesses, community groups, and others.

The decision to make adaptive learning technology a key part of Baltimore's Students and Teachers Access Tomorrow, or STAT initiative, was driven to a large degree by the desire to ensure an equitable education to children from economically-diverse communities. "Adaptive technology can help ensure that kids aren't penalized because of their zipcode or their race or what school they happen to go to", says Christina Byers, executive director of leadership development for elementary schools in the district.

Preparing the district for the new approach also took time. First, the county restructured the curriculum so it would work in the new blended model, and set the groundwork for the project by defining a lexicon of terms, to fill the gap left by an industry that tends to lump everything from narrow assessment tools to sweeping "intelligent platforms" under the term "adaptive learning". The district then introduced the products at a few "lighthouse" schools, starting with lower grades, before rolling anything out too broadly.

Meanwhile, there were many levels of training, starting with administrators and principals and moving down to teachers. One teacher at each school is trained to be a STAT Teacher acting as a local resource when problems arise.

Adaptive learning – in spite of the buzziness of the term – is just a sliver of what it means to add technology to the classroom. BCPS plans to have a digital device – a hybrid laptop/ tablet from Hewlett-Packard – or every student by the 2018-2019 school year. The district also created a steering committee to manage and coordinate the progress of eight different "conversions" that all need to happen in lockstep, including new kinds of curricula and the computer networks and teacher training to make it effective.

While the goal is to give more control to the students in how they want to learn, adaptive tools had to integrate cleanly with the overall learning management system, so teachers would be able to use them in combination with other digital and non-digital resources to help a specific student. The county also implemented ways that teachers could easily let the entire district know when bugs crop up, or recommend ways to change a program's user interface to make it easier to use.

If Baltimore County is any guide, providers of adaptive technology products will undergo some big changes as well. The district developed a detailed process for would-be vendors. Baltimore County hired the Center for Research and Reform in Education at Johns Hopkins University to do an extensive evaluation of the STAT initiative.

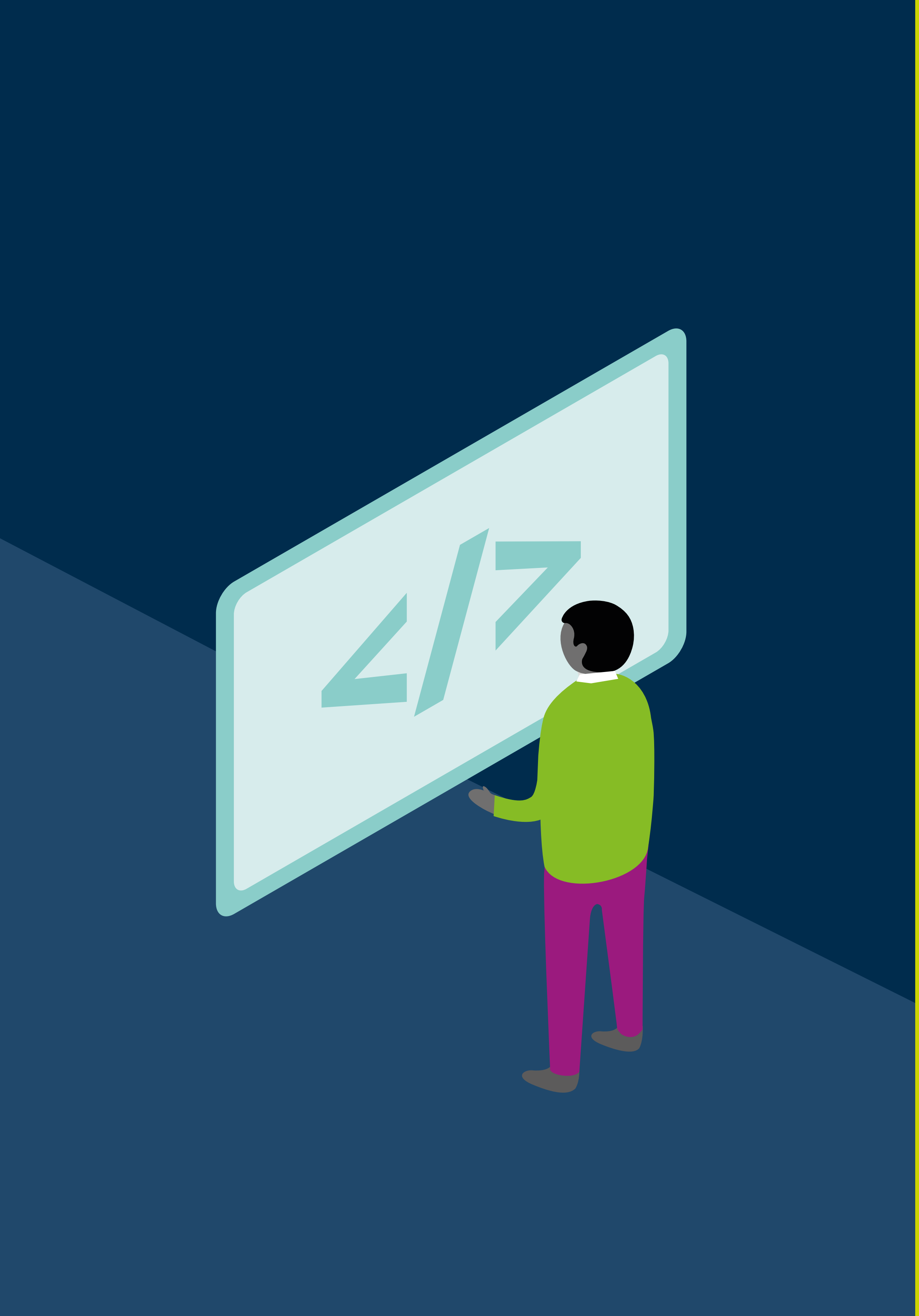
As a part of the assessment, the Center would appraise the effectiveness of the digital instruction tools as well as the changes they bring to teaching. "We'll sit through the sales presentations, but we know that building credibility in our district means showing our schools and teachers that something actually works", says Dr. Renard Adams, executive director of performance management and assessment at BCPS.

That was just the start. Big established players wanted the district to buy their full suites of tools and courseware, "but we wanted to take an 'iTunes' approach. We didn't want to buy the whole album - just the songs we wanted. That blew their minds", says Jeanne Imbriale, director of enterprise applications in the BCPS IT department. Many smaller companies couldn't - or wouldn't - meet the district's demand for extra staffing of support desks in the peak hours before and after lunch-time, or to have staffers on call after hours and on weekends, when many teachers are going through the data collected on student activity. "There was a lot of inflexibility on what many of the companies would and would not do," says Byers.

DreamBox is one of the companies that ran that gauntlet. It agreed to provide extra support and tweaked its licensing model. Rather than sell products on a per-grade basis, it agreed to a more flexible approach. After all, the point of adaptive learning is that every student can progress at his or her own pace. "We may have 'first graders' and 'fifth graders' who all need access to third-grade curriculum", says Byers.

DreamBox CEO Jessie Woolley-Wilson confirms that the company made these modifications, and others to boot. Since the company first started selling to schools in 2011, it has added more and more features as teachers have accustomed themselves to the program and aligned their instruction with it. "Now we call it an 'intelligent adaptive platform'", Woolley-Wilson says, emphasizing that teachers can use IT to create their own lesson plans. "There was an era in edtech when technologies were difficult to incorporate into classroom practice. We're going very quickly past that."

The story continues on page 54...



Designing Adaptive Learning Tools with Educators in Mind

After spending the past six months immersed in adaptive learning technology, we've learned quite a bit about not only its many promises, but also its shortcomings. Although digital adaptive learning tools promise better and faster learning, the educators and other experts we spoke with have real concerns about what's needed to make this technology complement what happens in the classroom.

Benefits: The Emerald City!

Adaptive learning is alluring because it promises to make learning better and faster. This combination is magnetic because it's aligned to an educator's ultimate goal of helping every student achieve his or her maximum potential through differentiation. Like the Emerald City in Oz, it's shiny, it's powerful, and it might be worth the journey it takes to get there.

Maximizing Learning

One of the touted benefits of adaptive learning is that students can work on only what they need when they need it, so that they get the most out of the time they spend using a tool, and spend more time in class in deeper meaningful interactions with teachers and peers.

The tools can take into account what students know now, rather than what they knew three or four months ago when they took a placement test. The ability to collect real student data and use it to automatically respond to a student's needs is what maximizes their potential for learning while using adaptive tools.

Precision

Another possible benefit of adaptive learning tools is the potential to provide increasingly precise recommendations and levels for students. This can be incredibly powerful for teachers, as they deepen their understanding of what students know and don't know. This can also give teachers more visibility into when and how to deliver precise interventions for individual students.

Challenges: The Field of Poppies...

Although there are many benefits of adaptive learning, there are also many challenges that can make it difficult for educators to implement. Most adaptive tools are used in learning environments that are led by teachers, which means they need to be able to work in harmony with teachers as the leader.

Ability for Choice and Control

Making choices and learning from those choices is an important part of the education process, for students as they learn, and for teachers as they design learning experiences. Often, students are able to demonstrate proficiency of a specific skill on practice questions but cannot then implement that skill in a project. In this case, teachers ask the student to go back and work on the basics involved in that particular skill. The implication for technology is that teachers want that level of flexibility in their digital adaptive learning tools.

Teachers we spoke to told us they want adaptive learning tools to give them the autonomy to occasionally override recommendations. They want the ability to be able to quickly review the content a student used in an adaptive tool, so that when a teacher needs to provide intervention for that student, he or she knows exactly what the student has done thus far. Reviewing the content helps teachers understand why students might be struggling. It helps them figure out other ways to teach a skill that might be more effective for a specific student.

Teachers also crave flexibility in terms of when they are in the driver's seat, and when the tool is. They want the ability to override or change features in adaptive learning tools based on the needs of their students and their courses. For example, a teacher might disagree with the skill a student is assigned and wish to change it. Or, they might want to adjust the level of mastery from 70% to 80% for an important course concept.

Most adaptive learning tools today do not allow teachers to change or even challenge the way the tool analyzes the student's performance or recommends new content. This can make it difficult for teachers to integrate holistically into their instructional design.

Fitting it into Real Classrooms

Adaptive learning tools are designed to support an approach to teaching and learning, whereby each student is working on only the skills that he or she needs. However, in order for adaptive learning tools to work successfully in real classrooms, they must be integrated with an appropriate pedagogical model, and an appetite and infrastructure for change at the system level.

For example, if a teacher uses curriculum with a strict pacing guide – outlining every objective the teacher must teach each day of the school year with frequent assessments and without flexibility or exceptions – incorporating a tool with an adaptive sequence into the classroom will most likely be unsuccessful. Tools with adaptive sequences allow students to work on any skill at any time, the tool's approach and the teacher's approach are in conflict.

How an adaptive tool is implemented in a school must align with how the tool was designed to be used, in order to be successful. For example, a tool with an adaptive sequence must be used in a learning environment that supports:

- Students working at their own pace.
- Students working on different content.
- Students working on different skills that might be above or below the grade-level expectations.
- Students working on skills in a unique order.
- Students working on skills that are different to the skills that are being taught in the classroom at the same time.

Building A Business

Despite decades of work, industry revenues for adaptive learning software were only around $200 million as of 2012 - the last time Kate Worlock, an analyst with the UK-based market research firm Outsell, tried to size the market.

The biggest portion of that has gone to New York City-based, Knewton, which has aggressively marketed its adaptive learning platform to deliver math, English, and biology courseware from a variety of publishers.

Other firms say they are starting to get traction. Boston-based Curriculum Associates, maker of i-Ready, has three million active users. Pearson's SuccessMaker also has approximately three million users. DreamBox, a ten-year-old company based in Bellevue, Wash., was used by 1.5 million students last school year, up from zero when it began selling to schools in 2011. "Our growth is a hopeful sign that there's more interest from school districts and more willingness to try new things", says Woolley-Wilson.

Some of edtech's biggest players are evidently hearing the same thing, and are moving more aggressively to embrace innovative technologies, including adaptive learning. Houghton Mifflin bought Scholastic's tech unit, and Pearson, has sold off the Financial Times and the Economist to focus more on education technology.

Maybe the best news of all is a new realism that's starting to infuse the adaptive learning community. There have been no break-out hits, from an investor perspective. That's weeded out many potential investors and entrepreneurs, as the realization dawns that this promising type of technology isn't likely to spawn the next Silicon Valley "unicorns" with $1 billion valuations.

"This is a 'some profit' business, somewhere between 'non-profit' and 'for-profit'", jokes Rob Waldron, CEO of Curriculum Associates, maker of i-Ready.

And nobody talks about technology replacing teachers anymore, or even about the ability of technology to raise test scores on its own.

"It all boils down to good teachers, good students, good parents and good principles", says Dr. Steven Ross, senior researcher and professor at the Center for Research and Reform in Education at Johns Hopkins. "Without that, some little software project isn't going to make that much of a difference."

Emerging Insights

The Current Adaptive Landscape

Many K-12 adaptive tools focus on math
If a tool has adaptive features and provides content, the content is most likely in math. For example, based on how tools identify themselves on the EdSurge Index, only 6% of language arts tools are adaptive, while 16% of math tools are adaptive. In addition, the 4 tools that provided content and had adaptive sequencing were all focused on math skills.

Adaptive content is popular in K-12
Of the K-12 tools we researched, 78% have adaptive content. For instance, LearnBop and Lexia both provide specific feedback for students and a high level of scaffolding and support when misunderstandings occur, so that students can work through problems until they get them right.

Adaptive sequencing is popular in Higher Education
Of the higher education tools we looked at, 67% have adaptive sequencing. This means that students can work on different content and skills based on their individual needs as they progress through courses. In addition, some tools allow professors to create their own content or upload course materials, while others provide content for the courses.

Collecting data and using data are different
Many companies communicate that their adaptive tools collect a lot of data. While this is true, not all of the tools actually use all of the data that is collected to adapt or respond to a student. Instead, the data that is collected is often displayed on a dashboard. Just because a tool collects a lot of data, it doesn't mean that the tool actually uses all it to adapt learning.

An Emerging Set of Valuable Product Features

Capacity to select the best content for students
It's one thing to recommend a skill, but it's another to recommend a skill and the best piece of content for learning that skill. Of the tools we researched that have adaptive sequencing, only 30% take the extra step of recommending content that's proven to be the best for students. Tools such as Knewton and Fishtree actually study how the content is used and how effective it is for students over time, and only recommend the specific pieces that are the most valuable for students' learning.

Capacity to collect data on how students learn
Answering a question correctly is important, but so is the process it took to get there. Some adaptive tools can collect data on how students learn and use it to create a more complete picture of their abilities.

For example, DreamBox is able to tell whether students use hints and manipulatives, also when they use them. This information is included in the decisions about whether a student really knows the material or not, and most likely leads to more accurate content recommendations.

Having a deeper understanding of students' abilities is very valuable, but so is teaching students how to develop effective processes for learning. The next generation of adaptive learning tools will be able to work out ways to help students improve their learning processes and eventually measure other skills that are important for learning such as motivation, creativity, perseverance, and self-regulation.

Capacity to use collected data to reveal how students learn
One of the benefits of large amounts of data on how students learn is being able to compare how educators think students learn, to how they actually learn. One way that adaptive tools are helping to do this is by capturing the order of skills that students are actually using to learn content. For example, Dragonbox is exploring the differences between the order in which students actually learn skills in math, to the conventional order of skills that are commonly used to teach K-12 math. If differences exist, this has the potential to improve the way educators teach math beyond the software.

What's Needed to Succeed Today + Tomorrow

After charting the trends, we have formed our own perspectives on what the future of adaptive tools might look like when scaled successfully. If adaptive learning is to reach its full potential to support teaching and learning, here are a few ingredients we would argue must be present.

Start with a clear educational vision
Just because adaptive learning is popular, does not mean that it is the right choice for everyone. The first step toward a successful implementation is having a clear educational vision or goal, and linking that goal to how these tools will be implemented. If these are in conflict, the adoption of adaptive tools will most likely be rocky.

The best adaptive learning includes teachers and technology
The most successful cases of teacher-technology partnership occur when adaptive learning tools are adopted in harmony with teachers' knowledge, expertise, and instructional approaches. As Chin Song, Director of Technology in Milpitas Unified School District told us, "The greatest adaptive mechanism is the classroom teacher. The data the tool provides should be used to provoke instructional changes in the classroom."

Because real learning is personal and social, teachers play a critical role in sparking student engagement and motivation, as well as coaching them in more open-ended content areas. In addition, adaptive tools can be like an ever-present teaching assistant, supporting students with instruction while capturing information that is hard for teachers to regularly collect. Working together will create the most positive learning outcomes.

Teachers need user-friendly data
Adaptive tools collect a lot of data and data is only useful if it is understood and acted upon. Therefore, adaptive tools need to be able to prioritize the data that is collected, and how to present it in an educator-friendly way. Moreover, many educators are using more than one product, especially in K-12. In order for the academic data to be valuable across several products, it needs to be calibrated against a common set of data standards.

There are many assumptions that need to be validated.
Adaptive learning has a lot of possibilities but there is still much to be learned. For example, how much change is the right amount of change to achieve the highest student outcomes? What impact does adaptive learning have on a student's ability to retain knowledge? Is a dynamically created learning path actually more effective and efficient for students over time? Often, the popular opinion is that more is better but there is still a lot that needs to be tested and validated before definitively stating that this is in fact true.

It is our hope that this piece provides parents, policy-makers, and educators with the right questions to test and validate these assumptions with creators of these tools. It is by asking better questions, that we will achieve better outcomes for our students.

Credits & Sources

Mark Brodsky, CEO, Adapt Courseware

Dr. Robert Dillon, Director of Innovation, Affton School District

Dr. Carol Connor, Professor, Arizona State University

David Robb, Supervisor of Innovative Learning, Baltimore County Public Schools

Linda Marchineck, Coordinator of Internal Assessment, Baltimore County Public Schools

Adam Kurtz, Principal, Clarke County School District

Dr. Jim Thompson, CEO, CogBooks

Nelson Gonzalez, Chief Strategy Officer, Declara

Dr. Tim Hudson, Senior Director of Curriculum Design, DreamBox Learning

Jason Markey, Principal, Leyden High School District 212

Terry Nealon, CEO, Fishtree

Aurelia Alvarado, Innovation Director, Innova Schools

Dr. Bror Saxberg, Chief Learning Officer, Kaplan

Anirban Bhattacharyya, Digital Learning Director, KIPP Foundation

David Liu, COO, Knewton

Bharanidharan Rajakumar, CEO, LearnBop

Alyson Deutsch, Senior Director of Educational Product Design, Lexia Learning

Dr. Rose Luckin, Professor, UCL Knowledge Lab

Daniel Tu-Hoa, Senior Vice President, Mathspace

Chin Song, Director of Technology, Milpitas Unified School District

Viraj Kamdar, Director of Online & Blended Learning, NYC Department of Education

Amit Patel, Principal, Owl Ventures

Dr. Johann Ari Larusson, Center for Digital Data, Analytics & Adaptive Learning, Pearson

Dr. Angie McAllister, SVP Personalized Learning & Analytics, Product Management, Pearson

Dr. David Porcaro, Director of Learning Capabilities Design, Pearson

Ty Roberts, Chief Sales, Marketing & Strategy Officer, Realizeit

Nate Kellogg, Director of Personalized Learning, ReNEW Charter Schools

Bharat Kumar, CEO, ScootPad

Dr. Michael Clifford, Founder, Significant Systems

Dr. Dror Ben-Naim, CEO, Smart Sparrow

Bailey Thomson, Director of School Design, Spark Schools

Mike Teng, CEO, Swing Education

Gates Bryant, Partner, Tyton Partners

Dr. Joseph South, Director of the Office of Educational Technology, U.S. Department of Education

Aoife Dempsey, CTO, Triumph Learning

Ben-Naim, D. & Counselman, G. (2014). Defining the Taxonomy for 'Personalized Education'. EdSurge.

Fain, P. (2014). Learning to Adapt. Inside Higher Education.

Feldstein, M. (2015) Personalized Learning is Hard. e-Literate.

Feldstein, M. & Hill, P. (2015). Personalized Learning is Not a Product. EdSurge..

Fletcher, S. (2013). Learning in the Digital Age. Scientific American.

Getting Smart Staff & Contributing Authors. (2015). Getting Smart on Next-Gen Learning Platforms. Getting Smart.

Hill, P. (2014). Adaptive Learning Market Acceleration Program (ALMAP) Summer Meeting Notes. e-Literate.

Lapowsky, I. (2015). This Robot Tutor Will Make Personalizing Education Easy. Wired.

Martin, C. (2014). Shaping a School System, From the Ground Up.

The New York Meyer, D. (2014). Adaptive Learning is an Infinite iPod that Only Plays Neil Diamond.

New Media Consortium. (2015). Horizon Report 2015 K-12 Edition

Office of Educational Technology. (2016). 2016 National Educational Technology Plan. U.S. Department of Education.

Oxman, S. & Wong, W. (2014). White Paper: Adaptive Learning Systems. DeVry Education Group.

Pea, R. (2014). The Learning Analytics Workgroup: A Report on Building the Field of Learning Analytics for Personalized Learning at Scale. Stanford.

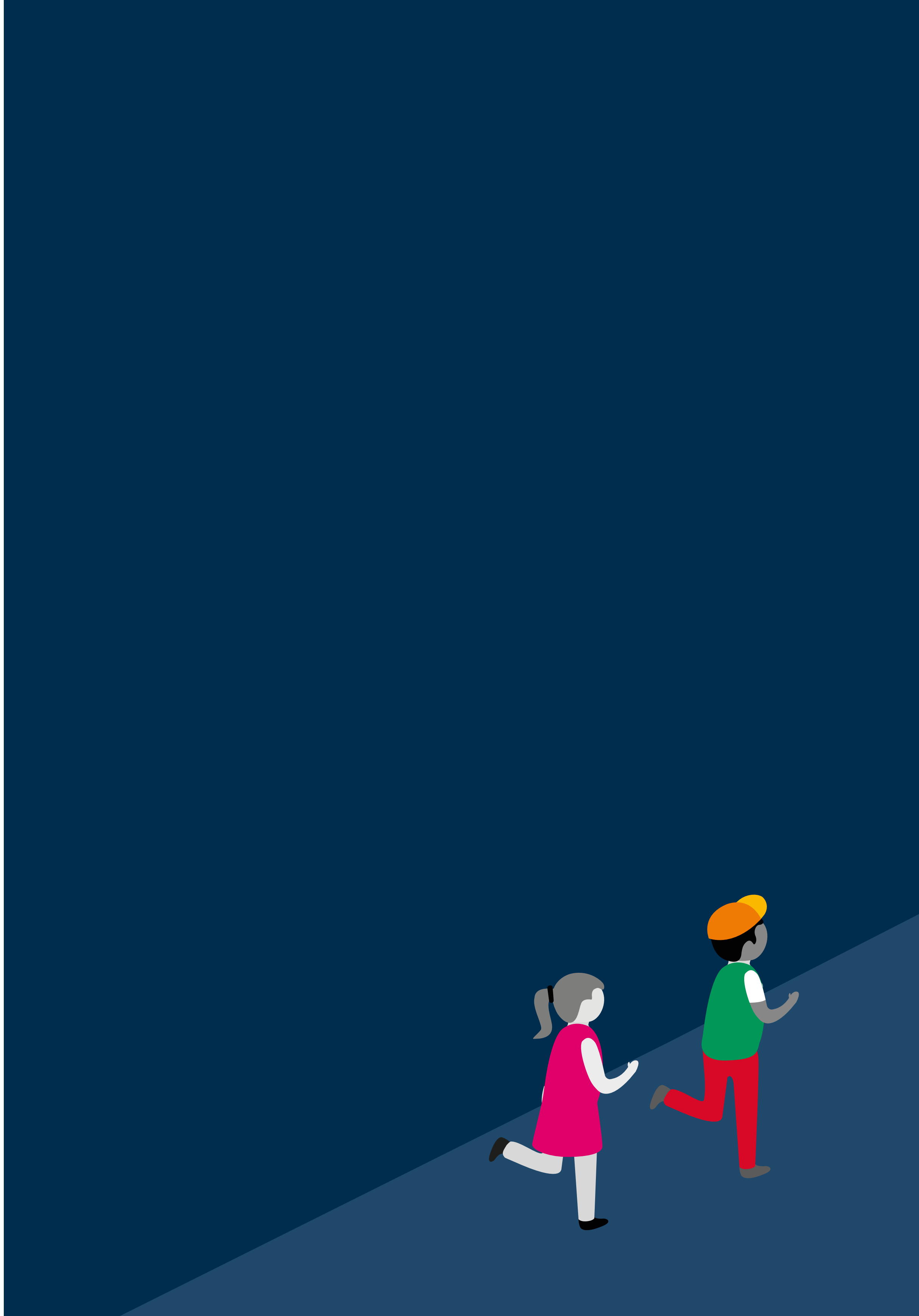
Riddell, R. (2013). Adaptive Learning: The Best Approaches We've Seen So Far. Education DIVE.

Newman, A. (2013). Learning to Adapt: Understanding the Adaptive Learning Supplier Landscape. Tyton Partners.

Chapman, D. & Mahlck, L. (Eds.). (2004). Adapting technology for school improvement: a global perspective. Unesco.

World Economic Forum. (2015). New Vision for Education: Unlocking the Potential of Technology.

Page 19 image: A third-grader learns with computer and books Photo Credit: Paty Gomes/EdSurge.



DESIGN BOND & COYNE

Pearson
80 Strand
London
WC2R 0RL

pearson.com

Join the conversation
@Pearson
#smartedtech
#adaptivelearning