







UNLOCKING POTENTIAL

An Insider's Guide to Adaptive Learning



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Unlocking Potential with Adaptive Learning Technology

Higher education is rapidly increasing in diversity, as students with a wide range of backgrounds, abilities, and needs enter the picture. At the same time, an emerging wealth of technology promises to help instructors meet the changing needs of their students. This progress comes with increased complexity in decision-making: before the explosion of educational technology, the main consideration was how to choose a textbook; now, there are difficult technology decisions to make too.

Evaluating the learning technology that goes along with the textbook involves deciphering often-misused terms that include adaptive, personalized, and individualized. This guide is designed to be a comprehensive introduction to the capabilities of the adaptive learning technologies currently on the market, their benefits for both instructors and students, and how to approach choosing the best option for your needs.



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Evaluating learning technology involves deciphering often-misused terms like adaptive, personalized, and individualized.

**What is Adaptive
Learning Technology?**

Clarifying the Terminology

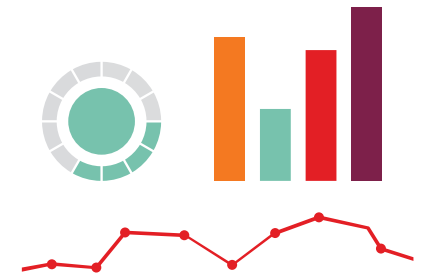
Some of the terms used in connection with adaptive learning are used interchangeably, and without clear definitions. The U.S. Department of Education's National Education Technology Planⁱ provides some useful definitions that can help to differentiate the concepts:

Individualization refers to the pacing of learning. Some students require more time to master a topic, or more repetitions in order to reach mastery; other students are able to skip sections or move faster.

Differentiation refers to changes in presentation that depend on the preferences of the student. For instance, some students may prefer reading individually, while others might prefer group discussion. Differentiation need not rest on the debunked concept of multiple intelligences; making allowances for student preferences can help with motivation.

Personalization refers to a comprehensive adjustment of all facets of a learning experience to individual needs. It encompasses individualization and differentiation.

Not all uses of these terms will adhere to these definitions, of course, but a clear set of definitions can help to assess systems that claim to offer personalized tools—are they really offering personalization, or just individualization?



What is Adaptive Learning Technology?

Adaptive learning technology is any system that collects information on a student's skill, knowledge and confidence levels, and uses it to change the material or tasks presented to that student. The goal of adaptive learning technology is to personalize the course to suit the individual's needs, by helping them improve in their areas of weakness, better retain what they have learned and progress through the course at a pace and in a direction uniquely suited to them.

Adaptive learning is not a new concept. Any learning experience that is adapted to the individual—whether in terms of pace, order of presented concepts, type of assessment, or other means—can be considered adaptive. Educators of all stripes have been striving to make their educational offerings adaptive for as long as there has been education. What is new is the technology that can allow instructors to offer adaptive learning at an unprecedented scale and with unprecedented efficacy.



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What is NOT Adaptive Technology?

Not all digital learning systems are adaptive. Some digital learning systems create tasks or assessments that provide a student with a set of questions, and then show the correct answer—or a hint—to students who answer a question incorrectly. These systems are linear: each student is shown the same set of questions, and **nothing about the system changes depending on how the students answer.**

Adaptive learning systems, in contrast, collect student input data through answer choices, content interactions or confidence levels. The system can then use each student's input to change the learning path for that student, creating a personalized learning experience.

Get the inside scoop on McGraw-Hill
Education's Adaptive Learning Technology.

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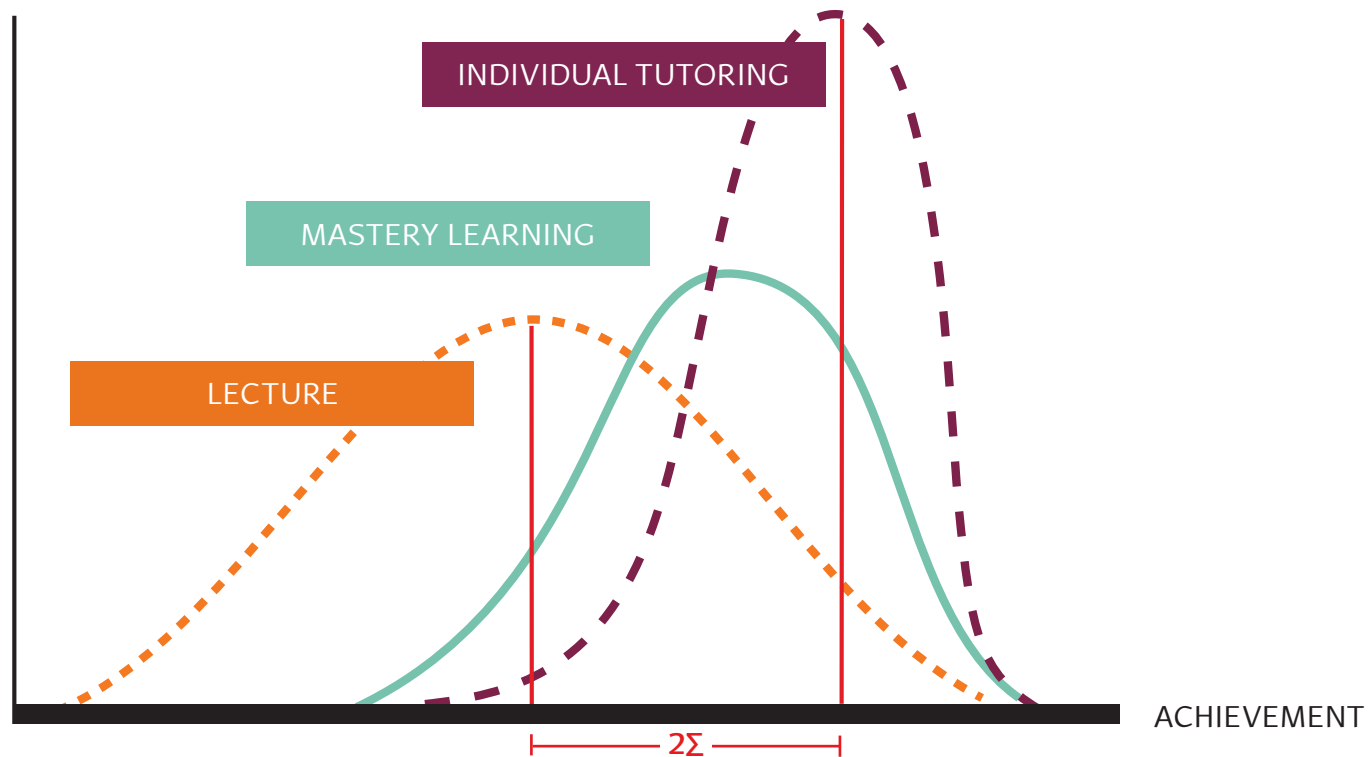
**The Educational Research
Underlying Adaptive Learning
Technology**

The Educational Research Underlying Adaptive Learning

In 1984, **Benjamin Bloom**—the educational researcher best known for Bloom’s Taxonomy—published a paper on the “2 Sigma Problem.”ⁱⁱ Bloom’s research divided students into three groups. Group 1, the control group [**Lecture Group**], received conventional class-based instruction and periodic assessments to track how much they had learned. Group 2 received conventional class-based instruction, but were given formative assessment tasks throughout the course, designed to help them learn the material and establish when they had mastered a topic and were ready to progress [**Mastery Learning**]. Group 3 received the same formative, mastery-based feedback as group 2, along with one-on-one tutoring [**Individual Tutoring**].



Bloom's results were striking. Students who had received individualized tutoring showed improvement over the control class by two standard deviations (or grades), with many of the tutored students surpassing 98% of students in the controlled group. Mastery learning, meanwhile, boosted results one standard deviation above the control group. The mastery students also surpassed 84% of the students in the control group. Furthermore, there was less discrepancy between grades in the test groups, implying that the students' results had a much lower spread, and were more tightly clustered around the average—that is, these techniques allowed low achievers to begin to catch up to high achievers.



The results, which have subsequently been reproduced and expanded uponⁱⁱⁱ, suggest that a combination of mastery learning and personalized tutoring allows learners to achieve their potential. These techniques can also play a substantial role in narrowing the achievement gap.

For Bloom, in 1984, this was a problem. As effective as mastery learning and personal tutoring were for learning outcomes, they were obviously vastly too labour-intensive to achieve realistically—it simply wouldn't be possible to provide every student with a personal tutor.



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Technology
can narrow the
achievement gap.



In the 21st century, technology offers solutions. By combining the power of software automation with the human insights and judgments of skilled educators, adaptive learning technology can provide mastery learning and individualized programs for students. This technology allows instructors to use their resources and time more effectively, stimulating student engagement as well as results.

Adaptive learning technology rests on other well-established concepts in educational psychology, with different systems utilizing different research.

[CONCEPT 1] Deliberate Practice



One of the most common bases for adaptive learning is the idea that it's the students who are most prepared to put in the effort who are most likely to reap the benefits. This concept has been given a variety of names, with subtle (albeit often important) differences between them, but the basic principle is consistent: conscientiousness^{iv}, grit^v, self-control^v, deliberate practice^{vi}, willpower^{vii}, and even the German word “Sitzfleisch” (literally translating to “sit-flesh,” and more commonly interpreted as “glued to the chair”) all have in common the notion that practising something difficult will eventually lead to success in that arena. Adaptive technologies are designed to make that practise efficient, constructive and rewarding.

[CONCEPT 2] Metacognition



Metacognition^{viii} is another concept that is central for certain adaptive learning technologies. This is the ability to think about one's thinking, or observe one's own learning. Flavell, the psychologist credited with developing psychology's understanding of the importance of metacognition in education, writes that "I am engaging in metacognition if I notice that I am having more trouble learning A than B; if it strikes me that I should double check C before accepting it as fact."^{ix}

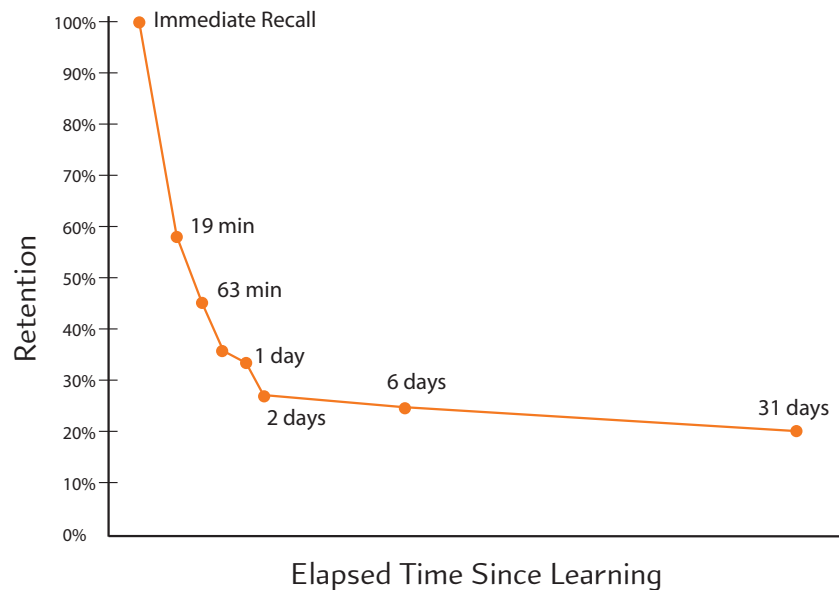
Enhanced metacognition has been found to improve students' understanding in a variety of disciplines, including mathematics, physics and reading comprehension, also helping to transfer skills to new settings.^x Adaptive learning can help students develop their metacognition by breaking down each skill into its component parts, monitoring their progress towards learning goals, repeating questions where they showed lower confidence and indicating discrepancies between self-assessed certainty and actual performance on a task. Highlighting these discrepancies can boost low confidence, moderate unduly high confidence, and determine when repetition is necessary – even with a correct, but guessed, answer. All of these strategies combine to give students a realistic view of their performance, and help them better understand their areas of improvement.

[CONCEPT 3] Ebbinghaus Forgetting Curve



It is also possible for adaptive learning technology to not only help students learn information, but also retain it. This is based on theoretical work with roots back to the 19th century, like the Ebbinghaus forgetting curve^{xi}, which mathematically models the rate at which people lose information after first learning it.

Some adaptive learning systems use these models to establish the best time for students to review information they have already learned, contributing to the long-term retention of information. Using these models also discourages cramming, which results in information being lost immediately after assessment.



**Under the Hood of
Adaptive Learning Technology**



There is now a huge variety of adaptive learning technologies on the market, all of which differ along multiple dimensions.

This section will explore these differences and take a closer look at:

1. How adaptive learning technologies differ
2. The basics of how adaptive learning technologies work
3. How adaptive learning technologies can best be applied to support teaching

Many adaptive learning technologies rest on the same basic set of fundamental principles, although how they apply those fundamentals can vary widely.

There are two main kinds of adaptive learning systems: those that are based on inference models, and those that are based on multi-compartmental models.

Inference models

Inference models get their names because they infer next steps by mapping the best pathway for students to learn a certain topic or subject. As time progresses, students complete more work and answer more questions, creating a map of pathways continuously growing in size. The answers students provide to these questions will determine their placement on the map and move them forward or backward along its pathways.^{xii} Many inference models are built on a content model, a learner model, and an instructional model.

A content model is based on an understanding of what has to be learned. For instance, a beginner's statistics course would cover a number of main topics, like probability, descriptive statistics, and random distributions. The system understands the links between these topics, as well as how to scaffold or support the student's knowledge within each topic. Because the system understands all the possible progressions through the course as a whole, its internal model of the topics looks like a complex 'map' (see Figures 1 and 2). Additionally, the paths through the content are usually defined and the content a student receives at each node through the pathway can be personalized to the student as they work towards mastery.

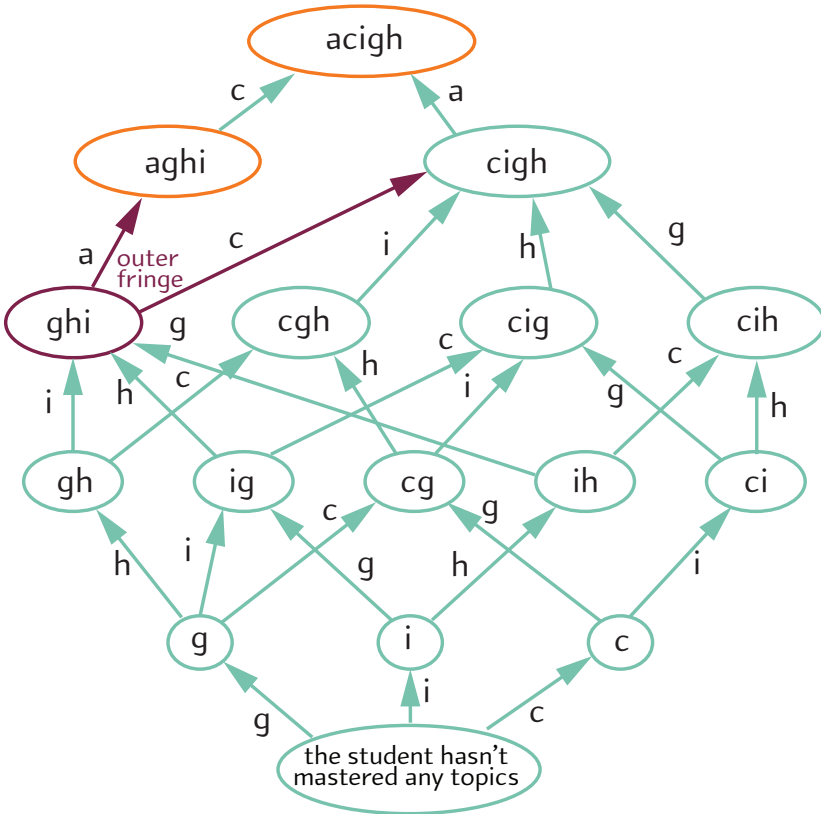


Figure 1: A representation of the content model of a small part (only 45 topics) of an algebra course in McGraw-Hill Education's ALEKS platform. At the bottom of the map, the student hasn't mastered any of the topics; at the top of the map, the student has full mastery of the course. At each stage through the map, ALEKS must decide how best to progress the student through the system.

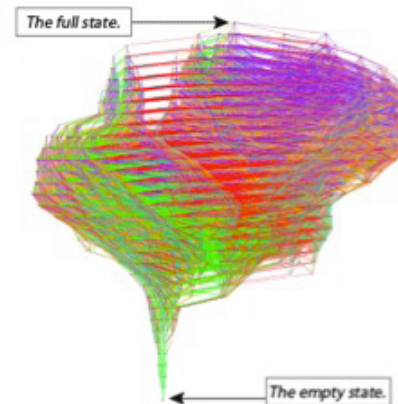
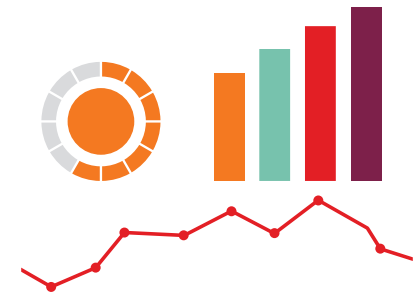


Figure 2: A representation of the content model of all 586 topics in ALEKS Algebra 2.

Both figures from https://www.aleks.com/about_aleks/tour_ai_pinpoint

The **learner model** is the system's understanding of what the student knows about the subject. A student beginning an introductory statistics course will first complete a task that assesses their grasp of background mathematical concepts so the system understands their existing level of proficiency when they begin. As each student progresses through the course, the system updates its model of what that student understands.

The **instructional model** determines how the content model and learner model come together: which parts of the content the student should be shown next, depending on their existing level of understanding. For instance, a student's path through an introductory statistics course will begin differently based on their initial assessment: some students will start out by getting up to speed on math, while others can jump straight in and make a start on the first topic they haven't yet encountered.



Multi-compartmental models

Multi-compartmental models, also called **biological models**, are designed to be more flexible than inference models.^{xiii} Where inference models map out a number of different learning pathways through the subject matter, allowing for some degree of flexibility in what content is presented to a student at any point, biological models are designed to adapt, incredibly quickly, to the vast array of possibilities in a student's learning path.

Creating a precise map of any given subject matter for any student is not only impossible, but unnecessary. In biological models, the semantic organization and process of making mistakes are used to help adapt the material to create a unique and changing learning experience. Biological models do this by having very detailed, semantically structured learning objectives, but less rigid connections between them than inference models.^{xiv} Depending on the student, the same learning objective can be achieved by taking different pathways.



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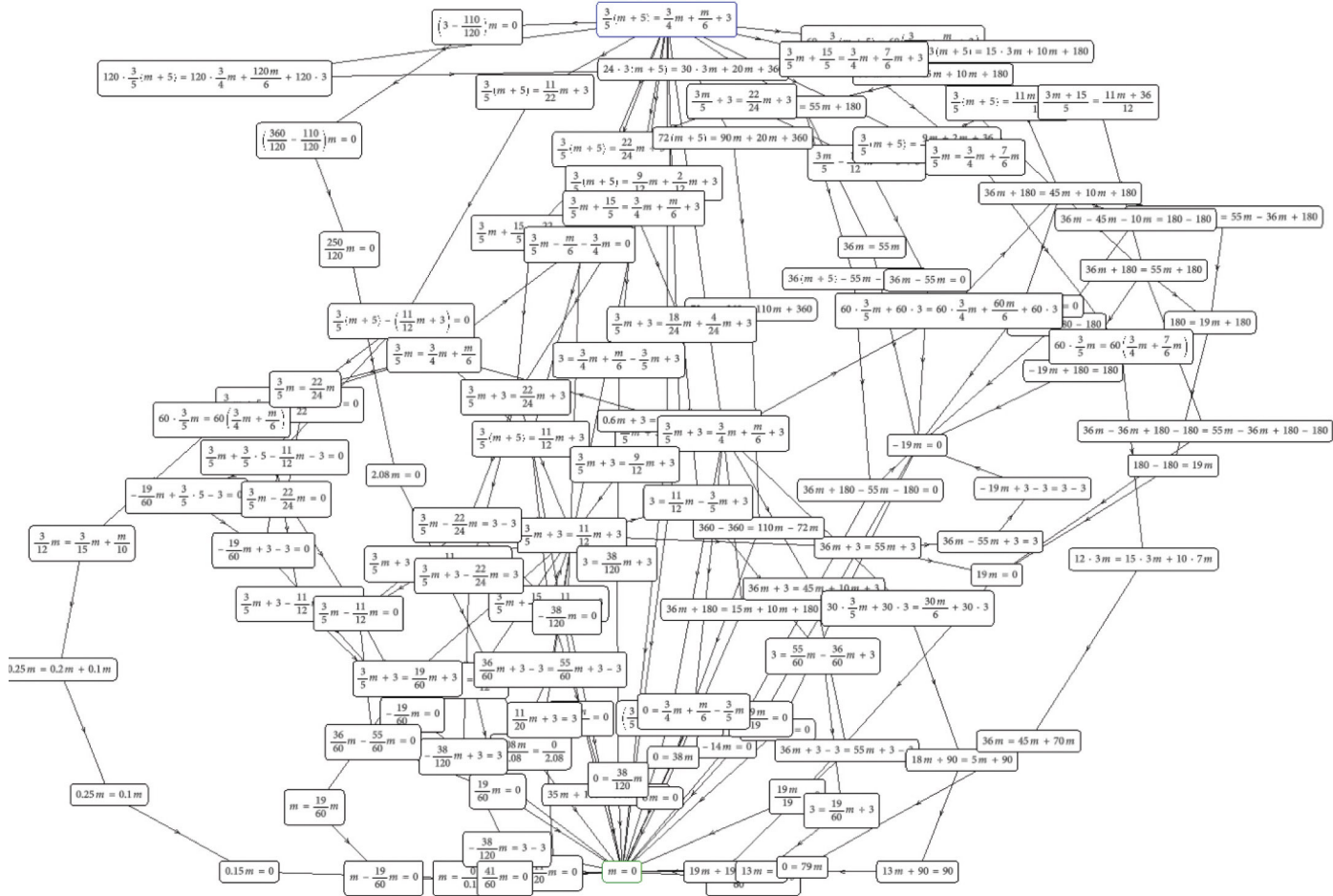


Figure 3: All the correct (but not equally efficient) pathways a group of students took to reach the answer of the equation at the top of the chart.

Biological models are designed to be able to cope with flexibility and messiness by accommodating “noise”—such as fluctuations in a student’s understanding from day to day, or ambiguity in how a question is phrased—and other uncertainty, such as answers that are mostly but not entirely correct, into their systems. Students’ learning is analyzed based not just on the correctness of their answers, but also on how long it took them to answer, how certain they were of their answer, and how long it took them to read the response to their answer.

These models are capable of making more fine-grained adaptations to each student, with more flexibility in making choices like the next step in the learning path, or what counts as “completion” of a section. The ability to handle uncertainty is a distinct advantage for subjects that don’t have clear-cut answers.

Want to take a peek under
the hood of Connect and
SmartBook?

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Questions to Ask When Assessing an Adaptive Learning Technology

Questions to ask when assessing an adaptive learning technology

1. What system best serves my subject area?



2. Does the system adapt to the student continuously?



3. How much does the learning path change according to individual needs?



4. What underlies the models, and how detailed are they?



5. What kind of student input is measured?



6. How does the system model the student?



7. How comprehensive and detailed is the adaptive content?



8. What platforms are supported?





1. What system best serves my subject area?

The first subjects to be comprehensively tackled by adaptive learning are those with clear-cut correct or incorrect answers and obvious scaffolding of concepts, the archetypal example being math. For example, McGraw-Hill Education's ALEKS platform is ideally designed for these kinds of subjects, and has expanded beyond math to other offerings, including chemistry and accounting.

Adaptive learning is also ideal for subjects that require a large amount of work on memory and repetition, including language learning and life sciences. Some platforms work well for these subjects, as well as subjects that sometimes don't have clear correct or incorrect answers, such as business, social sciences and humanities. McGraw-Hill Education's LearnSmart system, in combination with the SmartBook platform, applies adaptive learning technology to learning materials more often used in **business, life sciences, languages, social sciences and humanities**, helping students to efficiently work through large amounts of content.

2. Does the system adapt to the student continuously?

Some learning systems enable instructors to pre-assess their students' existing knowledge before the start of a course, and then tailor the course to the different student groups. For instance, a chemistry instructor could require all students to complete a pre-assessment of their knowledge of lab techniques, and then divide the class into those with lab experience and those who need to start out by learning basic lab techniques. These systems are sometimes called “predetermined”^{xv} or “macro-adaptive” systems,^{xvi} and they still rest heavily on the instructor to do most of the work in tailoring the course to the needs of different groups of students.

Other systems do the work of tailoring themselves, adjusting to student needs as the student progresses through the course. These systems are designed to be used continuously throughout a course, rather than only at the beginning, and constantly update their model of what each student knows, rather than resting on a single assessment at one point in time. **The information gathered by continuous systems is used to decide how a student should progress through a course, enabling a more genuinely individual—as opposed to group—approach to learning.**

Whether or not predetermined systems are genuinely adaptive is an ongoing debate in the field. Many definitions of “adaptive” include continuous adaptation as one of their core criteria, suggesting the consensus may be siding against predetermined systems being classified as adaptive.





3. How much does the learning path change according to individual needs?

Among continuous adaptive learning systems, there are differences in how frequently these systems alter the sequence of the material through which a student progresses.

Some systems don't alter the sequence at all, instead just supplementing information where it seems necessary for the student. For instance, a basic math system might have a defined progression through a set of topics (fractions, decimals, basic algebra, etc.) that can only be followed in a certain sequence.

These systems adapt to student needs on a more simple level. For example, if a student answers a question about fractions incorrectly, the system may pause and offer help in one or more ways: by suggesting learning materials like reading or videos, by providing hints, or by diverting the student into a learning exercise to break down the skill and learn it correctly before returning to the fixed learning path. This can work well for simple math courses, such as those in elementary school, but isn't suitable for more advanced courses or other subjects.

Other more advanced systems have the flexibility to change the sequence of tasks depending on how students answer questions. These systems may change in various ways: they could select questions to become progressively easier or more difficult depending on whether a student is struggling or flying through; they can alter the



sequence of skills that a student works on; or, in the case of biological models, they could select which learning objective should be pursued next, and choose the best way to achieve that objective at that particular point.

Within systems that are continuous, there are also important differences in how frequently they adapt to a student. Some systems might only adapt by deciding which section or assessment to present next, changing the learning pathway perhaps one to five times an hour the student spends in the system.

Other adaptive systems change more frequently. For instance, LearnSmart makes, on average, 120 adaptations per hour the student spends in the system—one every thirty seconds—to mould the course precisely to each individual student's needs.

4. What underlies the models, and how detailed are they?

The adaptive learning systems that are able to alter the sequence of topics differ in the sophistication and complexity of the rules that they follow. Some systems use a series of “if-then” rules to determine what should be shown to the student next. For instance, *if* a student answers a particular question incorrectly, *then* they should back track to a precursor skill. Although these systems are adequate for some topics, they often are not sufficient for complex courses found in higher education.^{xii}

Algorithm-based systems are substantially more complex. They use machine learning to constantly update the system’s understanding of the learning content in relation to the student. This allows the system to essentially make its own decisions about how a student progresses through the course, based on what it knows about this student, about other students, and about the material to be learned.

There are a number of different algorithmic systems available, and the particular kinds of algorithms they use—as well as the research those algorithms are based on—are among the most important differences between the systems. The majority of adaptive learning systems are inference models, as described earlier, which are suitable for certain subjects like math and chemistry. Biological models, as found in LearnSmart, are ideal for a wider variety of subjects.^{xiii}





5. What kind of student input is measured?

Algorithm-based systems have other important differences, including the kind of input they require from students. The easiest kinds of input to work with are multiple choice or true/false questions. However, these aren't always necessarily the best way to assess knowledge because the student can simply recognize the correct answer from the provided options.

Some systems go further than this. For instance, ALEKS requires students to enter the answer themselves, sometimes using on-screen tools to complete complex answers like drawing charts, or showing the steps they have used in calculating a particular answer. Systems like these are better able to assess not only whether a student is able to generate an answer rather than simply recognizing it, but also how a student arrived at that answer.

LearnSmart is able to ask a variety of questions, including ones that require the student to supply the answer, as well as those that require recognition, matching, ranking, or other skills. It can ask different questions around the same learning objective to ensure the student's answers reflect understanding of the objective, not just memorization of repeated questions. Incorrect and partially correct answers also prompt questions that probe the gaps in the student's knowledge.

Other data, such as the student's certainty when they answered the question, and how long they took to answer it, can also be gathered in order to shape the ideal next task. Finally, feedback from the students themselves, such as LearnSmart's feature allowing students to challenge questions or answers that they feel are incorrect, can also be used to refine the content over time.



6. How does the system model the student?

Adaptive sequences constantly collect data on the student's responses and analyse that data to adjust the learning process. The kinds of data collected depend on the content itself and can be varied. It could be as simple as recording which questions a student answers incorrectly and setting a threshold; for example, requiring that 80% of questions are answered correctly before the student moves on.

More complex systems gather more comprehensive data to allow better direction of the learning path, and more informative data for the instructor. LearnSmart's biological models, for example, take into account that learning is messy—students can forget information from one day to the next, or accidentally click the wrong button when answering a question. It also takes into account the student's own evaluation of their knowledge, because unwarranted confidence (a student being sure of an answer, but actually being incorrect) or unwarranted uncertainty (being unsure of an answer despite it being correct) can both give insight into the student's grasp of the material, and their own awareness of their skill level. This system is also able to predict the rate of a student's memory decay, presenting them with already-learned topics that are due for a memory refresh before they are forgotten.^{xiii}

The data gathered can also allow tools to compare one student's profile to other similar student profiles, and predict the best course of learning based on what has worked for other students.

7. How comprehensive and detailed is the adaptive content?

Some adaptive learning systems are essentially platforms for courses to be built onto them. The main advantage of these systems is that they allow for a large amount of flexibility in the course material to be presented. However, populating an entire content model is a daunting task, and is often likely to be more time-consuming than a single instructor is able to manage. For complex subject matter and adaptive learning systems, this is unlikely to be something that can be achieved for each individual course.

Other systems already offer their own content, in the manner of a traditional textbook used to supplement an instructor's own course material. These systems include those offered by established educational publishers, as well as newcomers to the industry.

Some adaptive learning systems use pre-built content based on pre-existing materials, such as existing textbooks. Others are built on content that was designed with the adaptive system in mind. This content allows for a more complex and comprehensive system, with content matching the goals of adaptive learning and allowing the algorithm to have a fine-grained understanding of the learning objectives. For these reasons, purpose-built adaptive learning content is always a better option.



8. What platforms are supported?

Most adaptive learning systems are designed to be used on a desktop computer. Some come as standalone applications, or as a web app accessed through a browser, or both. Other systems offer more flexibility, with mobile versions suitable for use on phones or tablets. Adapting the content and usage of the system for these different contexts is essential, so that the user experience is comfortable and seamless regardless of where it is being used.



Find out what makes McGraw-Hill Education's Adaptive learning technology different from everything else on the market.

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**Gathering Data and Insights
to Improve Student Performance**

One of the major strengths of adaptive learning is the amount of data gathered by the system.

Different technologies gather different kinds of data about students, depending on how they work.

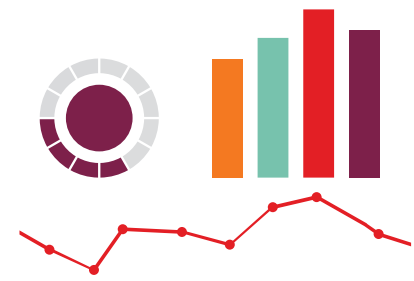
Some of the learning analytics available within adaptive learning technology include:



- ▶ Individual students' **performance** (for example, how many questions each student got correct on a particular assessment)
- ▶ Individual students' **engagement** with the system (for example, the time spent using it, how that time was spent, or the number of assignments submitted)
- ▶ What sections have been **mastered** by a student, and what sections, or how much of each section, still remain to be mastered
- ▶ Students' **improvements or deterioration** over time



- ▶ How sections, questions or objectives were received across a class group, helping to highlight what the class as a whole found easy or difficult
- ▶ Which questions have been missed or answered incorrectly the most
- ▶ Which learning objectives are the most challenging
- ▶ Individual assignments (for example, how many have been submitted, and average, high, and low scores across the class)
- ▶ Comparisons between students' performance, showing whether a student is ahead of the curve, or behind it
- ▶ Students' self-assessment of their own understanding
- ▶ Students' motivation and/or frustration
- ▶ Interaction between students within the system
- ▶ Skills that are needed to bolster performance



Adaptive system data provides actionable insights for both students and instructors.

For students, access to data like this is a huge step forward from simple, limited information like a single grade, or even information on which questions were incorrect. With learning analytics, students are able to gain insights that can actually guide their learning. Students can see which sections they struggled with the most (potentially difficult to spot in a test or exam that scatters questions from a single section, making it difficult to get a unified picture), where they are struggling to self-assess their knowledge, and what courses they should take to improve their learning skills.

For instructors, this is a far cry from simple, limited information like bell curves of student results—all these methods can tell instructors is whether course material is generally too difficult or too easy. Instructors can get a much broader and more granular review of their students' performance, not just a simple matter of questions right and wrong, but also whether students understand their own lack of knowledge, whether they are motivated and engaged, and whether certain sections are particularly problematic.



Aside from providing far more detailed information on *what* has happened, and allowing students and instructors to identify *why* it happened that way, learning analytics can also allow for prediction and extrapolation by modelling expected trends. This can allow both students and instructors to predict, for instance, how a student will perform in a particular section or course based on past performance.

Based on information like this, both students and instructors are equipped to make informed decisions. Instructors are able to give more personalized feedback to students, and deliver more precise interventions to students who are struggling. It can even help instructors identify students with low motivation who are at risk of dropping out, allowing them to intervene quickly. Adaptive systems are ideal for use in flipped classroom environments as the analytics can substantially qualify what a teacher should expect walking into the classroom thus allowing the instructor to focus on the lesson and higher level topics of discussion.



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With learning analytics, students are able to gain insights that can actually guide their learning.

Data reports and visualizations can also help instructors to adapt their own courses, improving their offerings after each course cycle. These reports allow for comparisons of how actual student results matched initial expectations, and information to help instructors understand why deviations from expectations occurred. They can also allow for comparisons between different courses that differed in small but meaningful ways, allowing instructors to make adjustments for each iteration of a course and improve it consistently over time.

The capabilities of data analytics in robust platforms extend far beyond just showing what skills students are struggling with, providing a comprehensive picture of student performance that takes into account motivation, confidence, and metacognition.

**Want to learn more about how
McGraw-Hill Education's
learning analytics can help you?**

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Benefits for Students and Instructors



The beauty of adaptive learning is that it caters to students across the entire spectrum of ability. Struggling students are provided with the support they need, while gifted students are able to bypass material they find basic, and spend their time on more challenging material.

With systems based on models of knowledge retention, students are able to spend more time working to learn or retain material they don't yet know or remember, rather than studying material they already know. In combination with learning analytics, students are able to develop their metacognitive skills, allowing them to understand their own learning more thoroughly. This individualized pacing and greater awareness are precisely what allows for the boosted results and reduced achievement gap found by Bloom.

Adaptive learning systems also have an important impact on student engagement, encouraging deliberate practice and creating tangible, incremental signs of improvement and progress. For all students, but especially those who struggle with confidence and motivation, this encouragement and visible progress can make or break engagement with—and success in—a course.

Adaptive learning is grounded in well-established pedagogical theory, but as a new technology, robust evidence of results are only beginning to be published. Early results indicate that the promise suggested by Bloom is being fulfilled by the best adaptive

learning technology, which results in boosted student performance and engagement. Some promising early results suggest that adaptive learning technology has the potential to improve student engagement and motivation,^{xvii} reduce course drop-out rates, and help students to achieve learning outcomes more efficiently.^{xii}

For instructors, one of the primary benefits of adaptive learning technology is the change in how effectively time can be used. Far from replacing the human element of education, the software liberates it. Instructors are able to offload tasks to adaptive learning software that would normally be spent on the repetitive and time-heavy task of grading.

Instead, that time can be spent learning how individual students are coping with the material, developing and recommending resources, and generally taking on the role of coach and mentor. Additionally, because students are able to receive better individual support on foundational concepts in their own time through adaptive learning software, class time can be used to work on higher level concepts, stimulate discussion and interaction, and focus on skills like critical thinking. This also means increased time for instructors to engage with students on an individual level, offering help where it is most needed.



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The beauty of adaptive learning is that it caters to students across the entire spectrum of ability.

The future of learning

Considering the diversity of students and learning styles, the spread of adaptive learning technology seems inevitable. By providing the benefits of mastery learning and a personal tutor without the added personnel or time, adaptive learning is impacting education on all fronts – from studying, to class prep, grades and more. The next step is determining the right adaptive learning technology for your needs and effectively implementing it.



Want to find out more about
the benefits of adaptive learning
for students and instructors?

Request a demo today!

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