MATH

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Intelligent Adaptive Learning

AN ESSENTIAL ELEMENT FOR PERSONALIZED LEARNING

Intelligent adaptive learning is defined as digital learning that immerses students in modular learning environments where every decision a student makes is captured, considered in the context of sound learning theory, and then used to guide the student's learning experiences, to adjust the student's path and pace within and between lessons, and to provide formative and summative data to the student's teacher.

This type of learning tailors instruction to each student's unique needs, current understandings, and interests, while ensuring that all responses subscribe to sound pedagogy.

Intelligent adaptive learning can play a critical role in raising the achievement of all students by meeting the individual learning needs of each student in PreK–12 schools.

Executive Summary

Imagine having access to a highly qualified personal tutor for every student in your classroom—on call, ready to tutor students anytime, anywhere. Intelligent adaptive learning is that, and much, much more. It is a sophisticated, next generation system that adapts learning to meet the needs of individual students, using the latest research from the learning sciences.

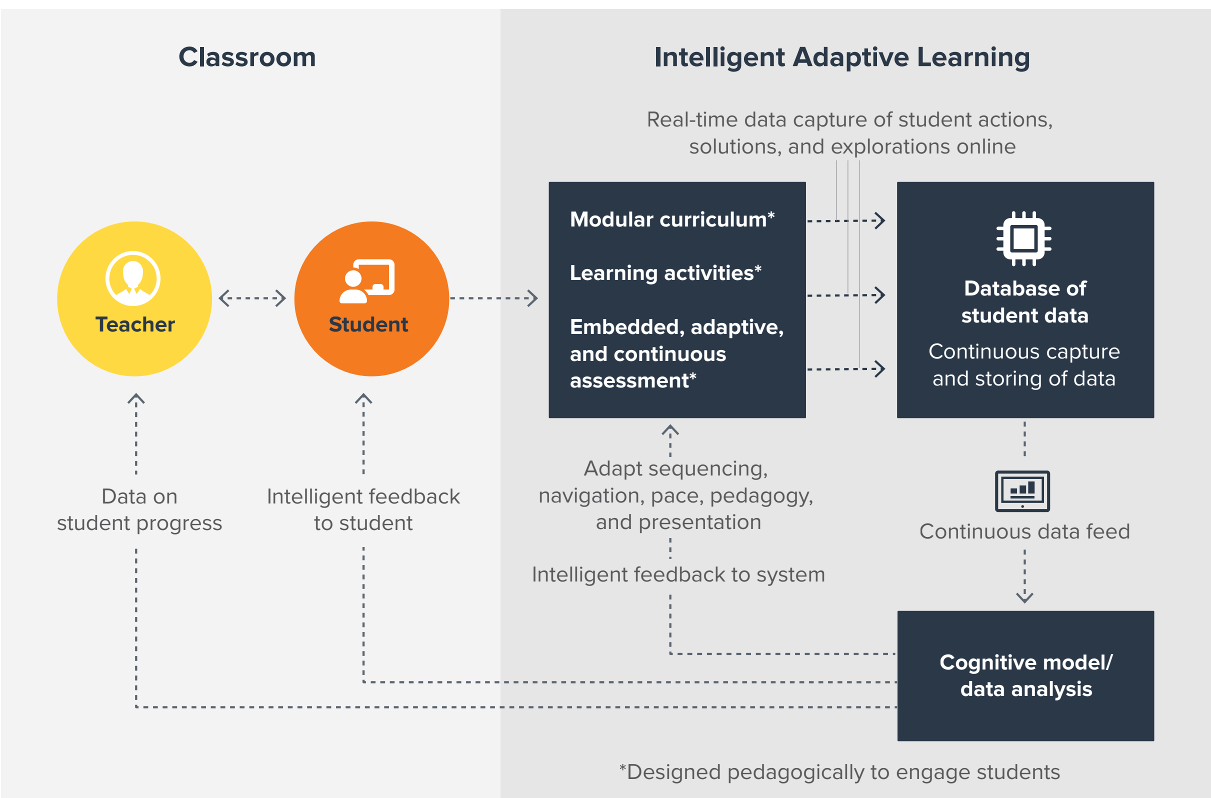
Intended as a supplement to the classroom, the intelligent adaptive learning system combines a modularized curriculum, a continuous stream of data as the student engages in the learning activities, and a cognitive model with which feedback is provided to the student and next steps are determined. Every decision a student makes is captured, analyzed in the context of sound learning theory, and then used to guide the student's learning experiences to an ideal degree of challenge—ultimately aiming for mastery. It adjusts the student's pathway through the modularized curriculum, modifies the pace, and engages the student in next generation instructional approaches that focus on deep understanding of the discipline, all while documenting the student's progress, and providing formative and summative data to the student's teacher. (See Figure 1.)

An intelligent adaptive learning system is designed to:

- Serve as a personal tutor to the student
- Adapt the sequencing of the curriculum and associated learning experiences
- Individualize the pace of learning
- Regulate cognitive load for the student
- Engage students in learning through gaming

Each of these design elements is supported through research. Together they serve as the rationale to warrant serious review of this genre of next generation learning tool by educators.[a]

Figure 1: A Model of an Intelligent Adaptive Learning System



Intelligent Adaptive Learning is Designed to:

1. SERVE AS A PERSONAL TUTOR TO THE STUDENT

Research indicates that tutoring provided by a highly qualified personal tutor is twice as effective as classroom instruction.[b] While this is a well-known fact, for most public schools such tutoring has been cost prohibitive.

An intelligent adaptive learning system is a next generation intelligent tutoring system that uses cognitive modeling to adapt what is presented to the learner, when it is presented, and how it is presented in response to the learner's needs.

This real-time feedback loop is key to the effectiveness of the system as a tutor. When used strategically, feedback can increase the average student's scores by 27 percentile points (effect size of 0.79). The aspects of feedback that had significant, positive effects on learning include: frequency of feedback, provision of formative feedback specific to the targeted learning objectives, and questioning/learning prompts[1]—all of which are incorporated into the design of intelligent adaptive learning systems.

2. ADAPT THE SEQUENCING OF THE CURRICULUM AND ASSOCIATED LEARNING EXPERIENCES

The sequencing of curriculum units and learning activities within units significantly influences the depth and efficiency of learning for students. In an intelligent adaptive learning system, different students use different paths. The system determines the options based on what a particular student is ready for and with awareness of the range and diversity of learning experiences needed to ensure coherent connections and deep understanding. The student is provided a degree of choice, but within parameters designed to ensure a consistent progression of learning.[2] Student choice is also an important element of these learning systems. Studies indicate that students who are provided choice have higher levels of engagement, which in turn correlates to more time on task and higher achievement.[3]

A key element of the individualized adaptive sequencing of curriculum is the importance of basing student experiences on their prior knowledge.[c] This not only enables the system to identify and correct the misconceptions a student might have, but it enables the system to present learning activities in ways that connect to and build upon that student's prior knowledge and interests. In addition, this adaptive sequencing of the curriculum enables cycling through the entire program of study to ensure eventual mastery.

3. INDIVIDUALIZE THE PACE OF LEARNING

This national trend toward student-centered learning challenges the notion of seat-time versus competency-based learning. It is clear from studies on tutoring that enabling students to work at their own pace to achieve mastery—with appropriate feedback through the tutor—is an effective learning strategy. In fact, researchers have found that mastery learning, where learning is held constant and seat-time varies, when compared with the opposite (seat-time held constant and learning varies) results in significant increases in student achievement.

4. REGULATE COGNITIVE LOAD FOR THE STUDENT

It is the responsibility of the teacher to adapt learning activities to ensure that students are making steady academic progress toward targeted learning standards. The range of prior knowledge and skill levels that students bring to the classroom is broad, but regardless of the students' starting points, the learning process should support the each student's steady progress toward the learning standards.

The area between these two points is called the student's "zone of optimized learning." Because this zone is different for every student, keeping each student within his zone is a challenge. If the tasks presented to the student are too complex for their skill level, they may become frustrated. On the other hand, if the tasks assigned are not sufficiently challenging for their skill level, they will become bored. Thus the teacher needs to continually monitor the student's learning experience to balance task complexity and skill level. Meanwhile, the curriculum should also present learning activities that build on the student's prior knowledge and interest areas. When expertly orchestrated, the balance between complexity of task and skill level will be challenging, yet comfortably paced by the student.

5. ENGAGE STUDENTS IN LEARNING THROUGH GAMING

Student engagement is a measure of a student's investment in learning as defined by their perseverance and willingness to exert effort necessary to comprehend complex ideas and master difficult skills.[4] There are a number of instructional and learning strategies that increase student engagement, including: a logical sequencing of curriculum, novelty and variety, student choice, intellectual safety (i.e., system assures the intellectual risks will not be ridiculed), affirmation of the work and progress, and clarity of goals.[5,d]

Interestingly, this list of strategies parallels the principles of gaming. It is ironic that students who struggle to focus on learning often have no problem playing strategy games for hours. The research on learning through gaming reports mixed results.

However, studies suggest that serious games that are effective in achieving positive results follow the five basic principles that are also key design features of intelligent adaptive learning systems:

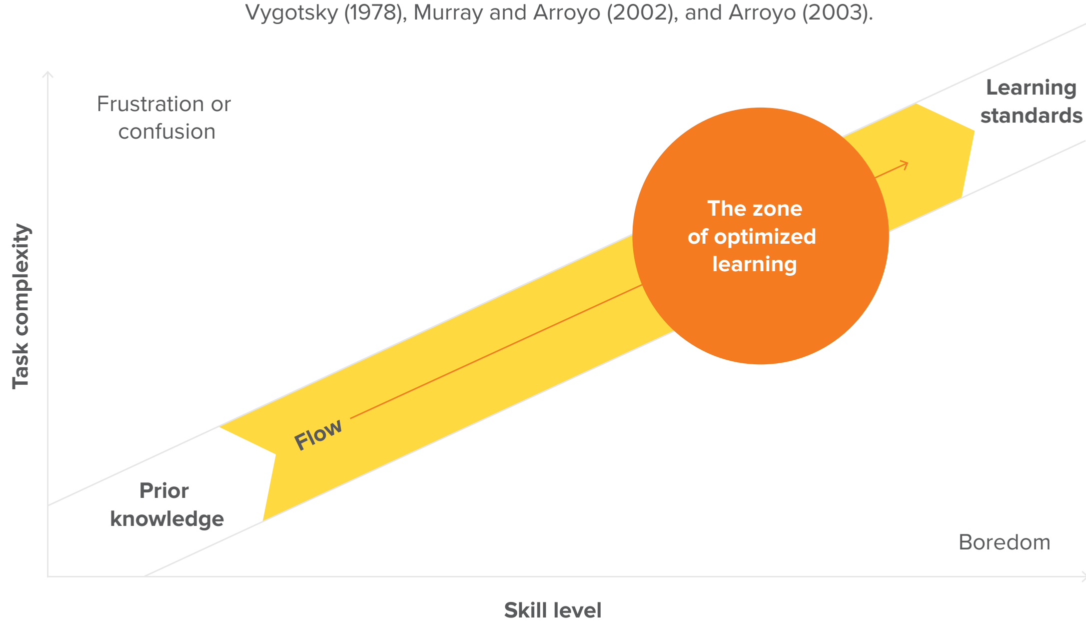
1. sequenced challenges
2. "just in time" and "on demand" information
3. performance before competence
4. motivation and attention
5. timely and specific feedback[e]

Thus, some intelligent adaptive learning systems use gaming to engage students in assessments, learning strategies, and learning activities that promote mastery.[f]

Intelligent adaptive learning is an extremely important asset in the pedagogical repertoire of the teacher/student team. It is important that educators vet each intelligent adaptive learning resource to ensure pedagogical alignment, and to plan carefully how intelligent adaptive learning—including the data on the student's progress—will be integrated into the larger learning environment.

Figure 2: Zone of Optimized Learning

Based partially on: Csikszentmihalyi (1991, 2000), Vygotsky (1978), Murray and Arroyo (2002), and Arroyo (2003).



Optimizing Learning

Teaching matters. Different instructional strategies within the classroom get different results. Today, although lecture is still a prominent instructional strategy in K12 schools in the United States, many teachers have begun to refocus their classrooms toward more personalized, active, inquiry-based, collaborative, and project-oriented learning.

Results in such classrooms vary, in part due to the expertise and experience of the teacher with these newer, more innovative instructional strategies. It is clear from research that the instruction and resultant learning strategies matter. Emergent research indicates that students who are taught by a teacher who is performing at the 75th percentile in terms of pedagogical excellence, will significantly outscore a matched group of students taught by a second teacher who is at the 25th percentile. In fact, an average student will score 14 percentile points higher in reading and 18 percentile points higher in math as a result being assigned to the first teacher instead of the second.[6] Make no mistake, an effective teacher—and their pedagogy—does make a significant difference in students' learning trajectories.[7]

Zone of Optimized Learning

To be effective, teachers must optimize learning for the many students in their classrooms. This is a challenge in today's classroom given the variability among students in terms of language, prior knowledge, motivation, literacy, numeracy, social/emotional maturity, and family support systems for learning. The Mathematics Common Core State Standards introduce additional depth and complexity to this challenge in their focus on deep understanding of concepts. Hence, to meet these standards, students will not only need to acquire facts, skills, and methods through memorization, building automaticity, and following algorithms (i.e., surface learning), they will also need to make sense of the subject area in context of the world around them and be able to transfer that knowledge to new situations (i.e., deep learning).

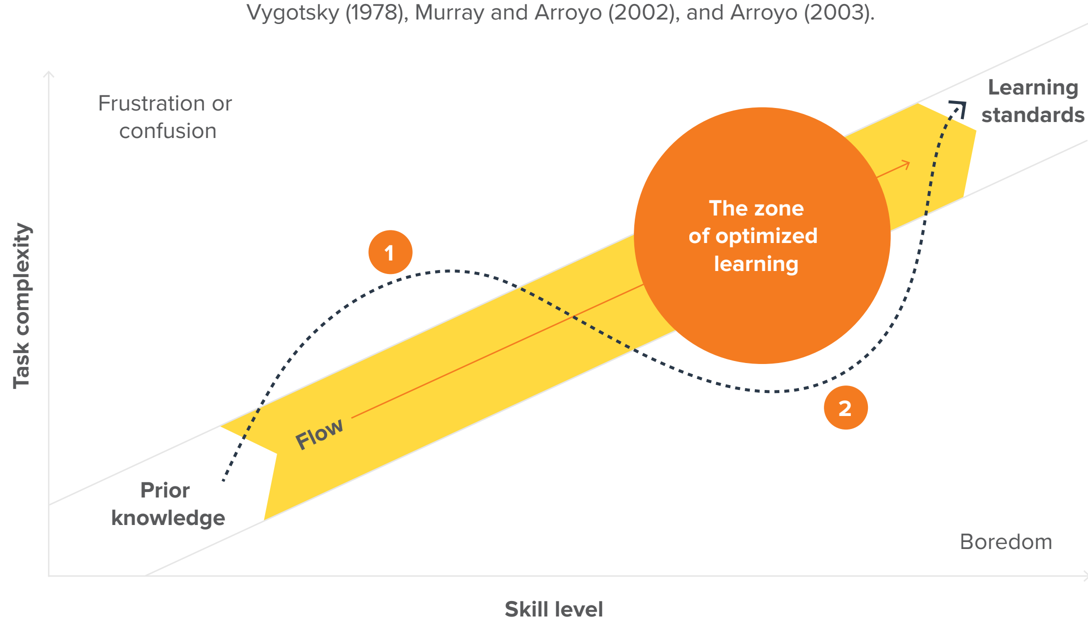
Such deep learning calls for cognitive effort on the part of the student, pedagogical skill on the part of the teacher, and sound instructional design of learning resources. Teachers do often differentiate assignments for groups of students and provide choice within assignments, which can lead to some degree of personalization and individualization. Anyone who has been in a classroom knows that every student's experience in learning a new subject is unique, due in part to the prior knowledge he brings to the situation. Schools often try to maintain a common class pace, but all too often, it doesn't sync with the needs of all students. Therefore, to optimize learning for each student, a teacher must continuously monitor, guide, and adjust for individual and varying learning trajectories. The challenge for the teacher is in designing the activities at a level that all students find challenging, but doable, given their wide range of prior knowledge and varying skill levels relative to the subject.

Consider this challenge from the perspective of the student. Each student has a zone of optimized learning that is grounded in the prior knowledge the student brings to learning, and culminates in the attainment of the targeted learning standard (see Figure 3).

The teacher must build on the wide range of prior knowledge that students bring to the classroom, scaffolding each through the curriculum toward the achievement of the targeted learning standard. To do so requires that the teacher balance the complexity of the tasks assigned to students with the students' current skill requirements, keeping them in their zone of optimized learning.[9]

Figure 3: Zone of Optimized Learning

Based partially on: Csikszentmihalyi (1991, 2000), Vygotsky (1978), Murray and Arroyo (2002), and Arroyo (2003).



One student's pathway through this zone of optimized learning[8] is shown below in Figure 3. [9, 10, 11, 12] The dashed line running through the figure represents that student's learning trajectory—note that the trajectory is not always within the zone. At Point 1, the task complexity is too low and it doesn't challenge the student, resulting in his becoming bored and demotivated. At Point 2, the complexity is too high for the skill level, resulting in the student becoming confused or frustrated, and again, demotivated to learn. Learning is optimized when the student stays within the zone of optimized learning by building on the prior knowledge he brings to the situation, thus making incremental progress toward the targeted learning standard.

One of the reasons for less-than-stellar academic performances by students is the lack of strategically designed learning experiences in response to situations where students find themselves at the boundaries of their zones. Often, the teacher is not there to provide the scaffolding and support the student needs when they need it. Moreover, especially at younger ages, students are often not sufficiently self-directed in their own learning to make the necessary adjustments, either cognitively—to manage their own learning—or emotionally— to stay motivated and engaged. The daily challenge is to ensure that each student stays within his optimized zone of learning.

Sound like an impossible job? Given that each student's optimized zone is also constantly shifting, it is extremely difficult for a teacher with 20 to 30 students to reassess and recalibrate each day, to provide the learning activities, and associated scaffolds, prompts, feedback, explanations, and guidance required for genuine personalization. That type of affordable, real-time responsiveness requires feedback loops and real-time data that only technology can provide.

The zone of optimized learning in a particular area of study is unique for each child. It represents the range of learning activities that will enable the student to make incremental progress from his starting point—defined by the student's prior knowledge of the topic and his current skill levels—to the end point, which is defined by the targeted learning standards. That endpoint includes both content and practice standards (i.e., knowledge and skill targets).

Intelligent Adaptive Learning

Intelligent adaptive learning optimizes learning by establishing a digital learning environment that keeps students in their optimized learning zone. It captures every decision a student makes and adjusts the student's learning trajectory both within lessons and across lessons. The key attribute of the intelligent adaptive learning system is not the immediate correction of every student error, but rather that it attempts to "identify the psychological cause of mistakes," provides intelligent feedback and prompts for reflection and rethinking by the student, and "thereby lower(s) the probability that such mistakes will occur again."[13]

Imagine a personal tutor who constantly checks for understanding in real-time by analyzing large datasets of a student's actions and interactions, often comparing them to a knowledge base of known misconceptions or errors commonly committed by other students studying the same topic. This tutor provides multiple pathways to learning with real-time intelligent feedback and access to progress reports for students, teachers, and parents. Intelligent adaptive learning systems often include feature sets that students find engaging. Examples include gaming, or providing students a modicum of choice as to which activities they pursue—within set parameters of their current level of expertise and their targeted goals.

Inherent in the design of intelligent adaptive learning systems are five critical factors:

1. the content in the form of lessons or activities in which the learner engages in a sequence unique to his needs
2. the instructional strategies that teach and guide the learner
3. measurements of the affect of the student toward the learning
4. mechanisms for measuring and understanding what the student does or does not know
5. a feedback mechanism whereby the data acquired about the learner informs the next round of content, instruction, and motivation the student encounters[14]

The first time the student uses the intelligent adaptive learning system, they take an adaptive assessment that places them within the modularized curriculum. From there, the student's pathway through the curriculum, their pace of learning, and the feedback they receive are responsive to the individual student's needs and experience. The student has intelligent personalized support, which adapts the sequencing of the curriculum, the pace, pedagogy, and presentation of lessons to optimize their learning. All these adaptations are in response to their actions and reactions within the system. See Figure 4 for a visual description of the student's experience, feedback loops, and cognitive modeling that guide the student's intelligent adaptive learning experience.

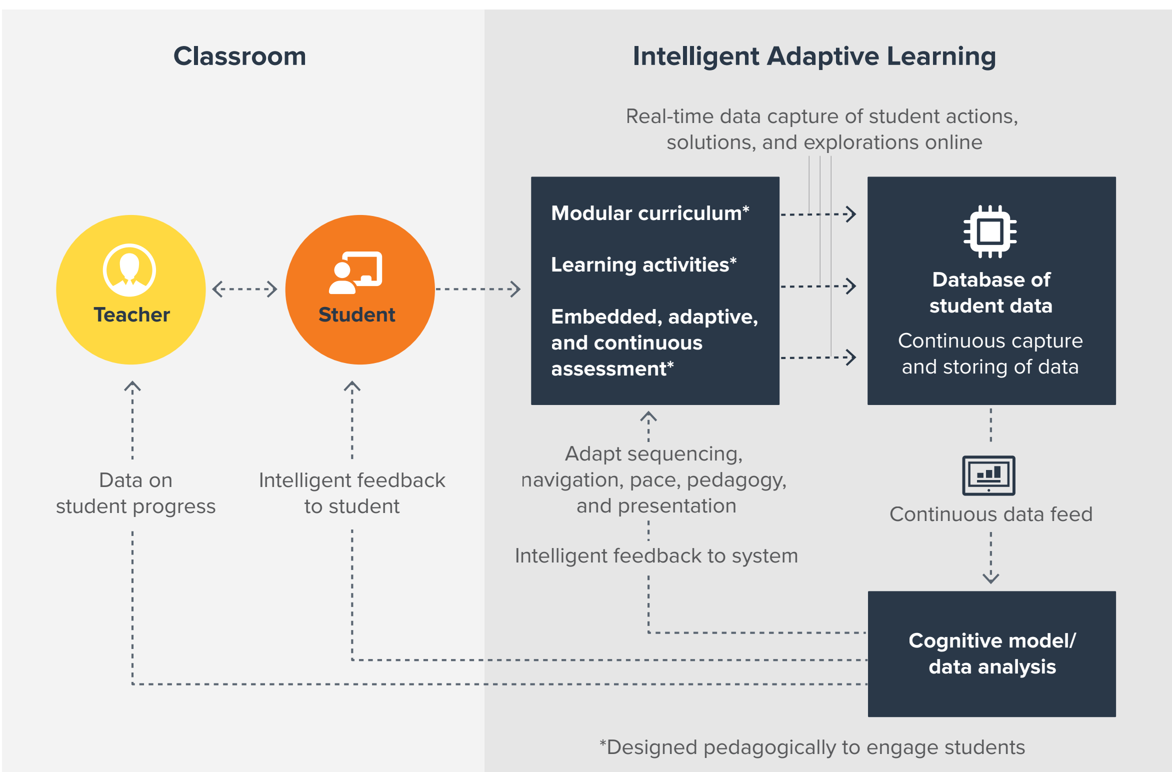
Many teachers use intelligent adaptive learning to provide students with individualized tutoring that guides the students in their learning of specific topics. These teachers have access to detailed reports on the progress students are making on the learning standards.

The level of sophistication of today's intelligent adaptive learning systems is far superior to similar technologies of the past. Computer-assisted instruction (CAI), adaptive hypermedia, intelligent tutors, computer-supported collaborative learning (CSCL), and individualized learning systems (ILS) of the past typically lacked the speed and sophistication of today's intelligent adaptive learning systems.[15] The processing speeds, advanced learner analytics, and sheer magnitude of data collected and analyzed, combined with the sophisticated models of cognitive development, optimize the learner's experience. The current day intelligent adaptive learning systems readily adjust instruction, content, and motivation based on a student's current state of prior knowledge, expertise and skill levels, and readiness for progressively advanced complexities of learning.

Cognitive modeling is the lynchpin of the system. The genesis of the cognitive modeling that enables intelligent adaptive learning is based on advances in artificial intelligence (AI) systems. These AI systems were built to utilize a set of knowledge-based expert rules to mimic the behavior of experts. Intelligent adaptive learning systems also use such symbolic representations to continuously monitor and guide the user experience in ways that optimize the learner's experience.[16] Inherent in the cognitive model is the determination of the level of mastery required of the student in order to move on to new curricular units; a pedagogical philosophy of how much scaffolding (intelligent feedback) to provide to the student, and when to provide it; the logic in the sequencing of curriculum units and lessons presented to the student; and the process by which the system determines the student's optimal learning style and subsequently presents the content to the student.

The very name of this learning resource—intelligent adaptive learning system—implies that the system combines intelligence and adaptivity. In fact, both are essential elements, and both are based in sound educational research. The intelligence aspect is embodied in the cognitive modeling, which combined with the continuous, real-time collection and analysis of user data, results in intelligent feedback to the user.

Figure 4: Classroom Environment Leveraging an Intelligent Adaptive Learning System



This continuous stream of intelligent feedback is provided to the user to keep him on a positive learning trajectory. The data stream is also used by the intelligent adaptive learning systems to determine whether the user is ready to move on to new curricular units, and based on the user's progress, it determines which curriculum units would optimize his learning trajectory. A third way that these data are used is in the reports made available to the teacher. While teachers will utilize the system in different ways, ultimately, each teacher-student pair is responsible for maintaining a positive learning trajectory for the student toward mastery of the targeted standards. Teachers typically consider the intelligent adaptive learning system as only one of multiple learning strategies and resources that ensure this goal is reached.

The elements of intelligent adaptive learning that contribute to the "intelligence" attribute include the following:

- Intelligent analysis of a student's solutions. The system interacts with the student by analyzing the data from the student's actions as he solves problems, explores concepts, and makes decisions. The system not only can tell what is wrong, but is also sufficiently intelligent to pinpoint where the misconception or misunderstanding occurred that is causing the error.
- Interactive problem solving support. The solution analysis described in the previous paragraph enables the system to provide extensive, detailed feedback and provides prompts to the student that cause them to rethink their strategies and solutions, and ultimately correct their own misunderstandings or mistakes. This "intelligent help" includes hints that prompt reflection on the problem and its context when a student is stuck. The intelligent adaptive difference lies in viewing these hints as an opportunity for critical thinking as opposed to simply "telling" a novice student what the "next step" of an expert's strategy would be. In this way, the system emulates the actions of an effective tutor.

  Intelligent adaptive learning systems are built around a modularized curriculum that is individualized for and by the student.

The elements of intelligent adaptive learning systems that contribute to the adaptive learning with those curriculum units and lessons include the following:[17, 18]

- Curriculum sequencing. Based on the intelligent analysis of a student's gains in knowledge and understanding, the system sequences the student's progression through the modularized curriculum. This is done by providing the optimal planned sequence of curriculum units as the student demonstrates readiness, and the customization of learning tasks with varied pedagogies within the module, again based on student data.
- Multiple learning experiences. The intelligent adaptive learning system typically provides multiple pedagogical approaches to teaching each concept. This includes a variety of learning experiences, activities, and contexts. The research on deep learning indicates that these multiple experiences are necessary in order to achieve the student's deep versus surface understanding of the concept. Encouraging and enabling deep learning requires that the tasks be meaningful, at an optimal level of difficulty for the student, and contextualized in ways that enable students to build schemas so they can make sense of the concept within the world around them.
- Customized presentation and pace. The system accumulates information about the student that is then used to dynamically generate and present digital content to the student. Diagnostic, adaptive assessments are embedded within each lesson to assess mastery in a fluid, transparent way that doesn't create anxiety for students. The system varies content, sequencing of content, and format as it optimizes the experience for the learner, frequently offering variations in the way learning activities are presented—which is often necessary to develop deep understanding. Typically, these learning activities are filtered to align with learner preferences. However, the longer a student stays in a module, the more alternates they may experience as they strive for mastery. As a student progresses through the system their pace is determined by how quickly they demonstrate mastery of a concept, thus pace varies across learners.

The 2 Sigma Challenge

Can we get the learning results attainable through tutoring, but in a cost effective way?

The research has been clear for over a quarter of a century, students who engage with a tutor in a one-to one situation significantly outperform students taught in conventional classrooms using lectures, and also in mastery learning.[h] The differences are truly significant. A student scoring at the 50th percentile in a conventional classroom, if tutored full time, would score at the 98th percentile on the same material. This is two standard deviations (sigmas) above the lecture method, thus the researchers labeled it the 2 sigma challenge (i.e., how to achieve these same achievement levels through group instruction).

A study by Bloom and colleagues demonstrated that academic achievement is less about prior achievement or aptitude, and more about the type of instruction the student receives. In Figure 5, the blue, yellow, and orange lines (left to right) comprise the student scores for the three instructional approaches, respectively, lecture, mastery learning[i] and individual tutoring.[19] All are bell shaped curves, but the individual tutoring results in higher scores relative to the other two instructional approaches.

Consider the score of the average student in each type of learning; the average student's score would be positioned on the chart at the peak of each curved line. As the chart indicates, if the student were taught through lecture, his achievement score would be significantly lower than if he were engaged in mastery learning or individual tutoring.[20] Over time, the 2 sigma challenge has raised a number of important questions. First and foremost, "What are the critical elements of tutoring that contribute to the significantly better results?" And second, "How can we achieve these same results without the expense of one-to-one tutoring?" (i.e., within the current time, budget, and teacher-student ratio constraints of the existing system).

Regarding the first question, researchers have identified critical elements of tutoring. They describe a tutoring framework consisting of five steps:

1. tutor asks an initiating question
2. student responds
3. tutor provides feedback as to the accuracy of the response
4. tutor scaffolds to improve or elaborate the student's answer in a series of exchanges
5. tutor gauges student's understanding[21]

Analyses of tutorial sessions looked at critical elements of tutoring that contributed to shallow learning (acquisition of facts, processes, or methods), and to deep learning (sense-making and transfer), both of which are important to attainment of learning standards.[j] The researchers reported:

- It was the active learning by students that influenced the level of learning more than the specific action taken by the tutor. The more constructivist the student response (e.g., spontaneously self-explaining, asking questions, drawing, taking notes, summarizing), the deeper the learning.
- Explanations by tutors resulted in shallow rather than deep learning. The researchers speculated that this might be due to a shift of the tutor's focus from the student to the content, thus eliciting less active learning by the student.
- The most significant increases in deep learning were a result of the students' self-reflective comprehension monitoring (i.e., students continuously gauging their understanding of the material).

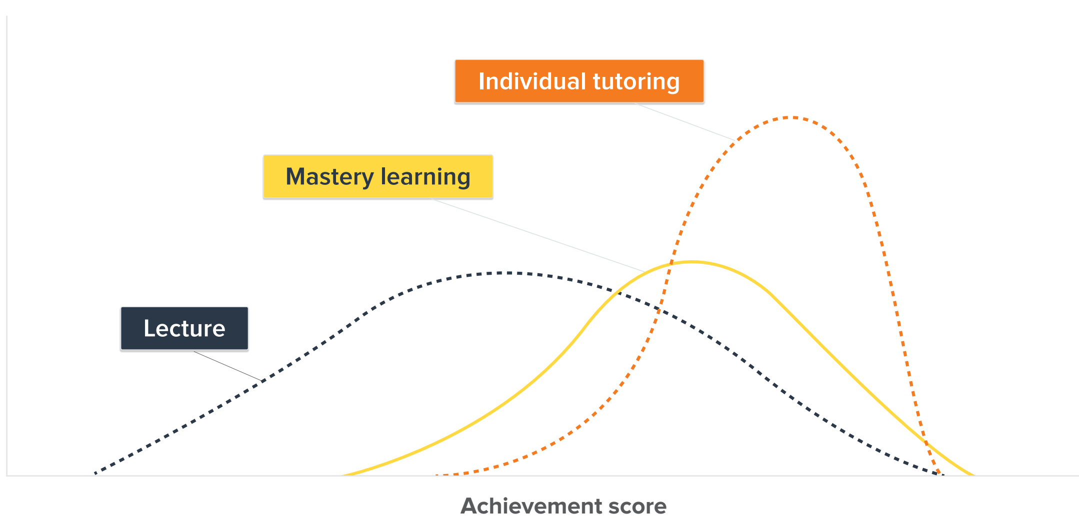
Interesting to note, the learner actions that did not produce increased achievement were those that the students initiated themselves, such as self explanations. Overall, the study found that the significant learning gains accomplished through the tutoring sessions are a result of the student-tutor interactions.

Finally, after decades of research, there are some answers to the second question, "How can we achieve these same results without the expense of one-to-one tutoring?" (i.e., within the current time, budget, and teacher-student ratio constraints of the existing system). The question has caused researchers to question whether the 2 sigma effect is accurate. Some researchers suggest that the effects of human tutoring are more typically in the range of +0.79, perhaps extending to 2 sigmas in special circumstances. These researchers explain that Bloom's 2 sigma data were skewed upward due to the use of a combination of human tutoring and mastery learning. Second, the use of computer-based tutors and adaptive testing, and adaptive learning have evolved over the last 20 years.

Given the power of today's next-generation adaptive learning, it is not surprising that researchers looking into the 2 sigma challenge are finding that the results from computer-based systems approximate those from human tutoring.

Figure 5: Differences in Academic Achievement for Students Taught through Lecture, Mastery Learning, and Individual Tutoring

Source: Bloom et al., 1984 as cited by Koller, D., Stanford University, at TedGlobal 2012.



The Research Behind Intelligent Adaptive Learning

Educators have been seeking a cost-effective way to provide individualized tutoring for decades. Technology now makes that feasible through intelligent adaptive learning.

Essentially, the intelligent adaptive learning system is an intelligent program that “listens to and observes” a student’s interactions with the learning activities from curricular lessons; it then analyzes that data, interpreting it through the lens of its cognitive model. This enables the system to provide intelligent feedback to the user, to determine the sequencing of curricular units and lessons, to make decisions about the sequencing of activities within a lesson, and to inform the educator through data reports on the student’s progress. The adaptivity is accomplished as the system applies the cognitive modeling to interpret the user data pedagogically, using that interpretation to adapt instantaneously within the lesson, adapt the sequencing of curriculum, filter and select learning activities, customize the presentation, adjust the pace of learning, and adapt the navigation system.

The design elements of the intelligent adaptive learning have great potential for increasing the pace and depth of student learning including:

1. the effectiveness of support, through the continuous stream of intelligent, formative feedback to the user, the system, and the teacher
2. the individualized, non-linear sequencing of curriculum and learning experiences
3. the individualized pace of learning
4. the regulation of cognitive load
5. student engagement through gaming

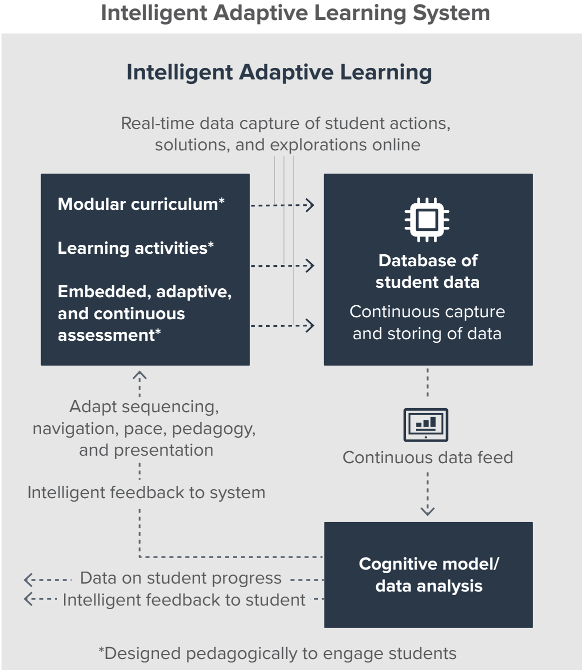
The research basis for each is discussed on the following page.

1. The effectiveness of support through a continuous stream of intelligent feedback to the user, the system, and the teacher

The reason tutoring works stems back to the strategic use of feedback. When feedback is specific to learning objectives, it has a powerful impact on learning. Feedback via computers has been found to be less threatening than face-to-face situations.

That translates into increased attention paid to learning on the part of the student.[22] In 2010, Wiliam argued that effective feedback can double the rate of learning. In his discussions on effective forms of feedback, Wiliam identifies five categories provided pedagogically: 1) clarifying learning intentions and sharing criteria for success, 2) engineering effective classroom discussions, activities, and tasks that elicit evidence of learning, 3) providing feedback that moves learners forward, 4) activating students as instructional resources for one another, and 5) activating students as the owners of their own learning.[23] The feedback within the intelligent adaptive learning system focuses on but one of these five categories; category 4 is excluded since intelligent adaptive learning systems are built for individual users, with no collaboration or cooperation among or between users. In 2010, meta-analyses by researchers from McREL[24] reported that, on average, the provision of such feedback increased student results by 28 percentile points for the average student. Alternative forms of feedback in the form of praise or extrinsic rewards were associated with little to no significant increase in learning, or in some cases with actual decreases in learning. The one exception to this was verbal praise, provided it is specific and sincere, with reference to accomplishments through student effort.[25]

Figure 6: Design Elements of Intelligent Adaptive Learning System



Researchers have also found that if the feedback is to impact learning positively, it must be focused on the specific task on which the student is working, hence the value of the realtime, intelligent feedback to the student. Furthermore, the feedback must be substantially more than simply an indication of a right or wrong answer, and go beyond a quantitative evaluation to qualitatively address how a student arrived at his answer. A meta-analysis on formative assessments found increasingly positive results in student outcomes as the feedback becomes more specific and more closely associated with the specific activity in which the student is engaged.[26]

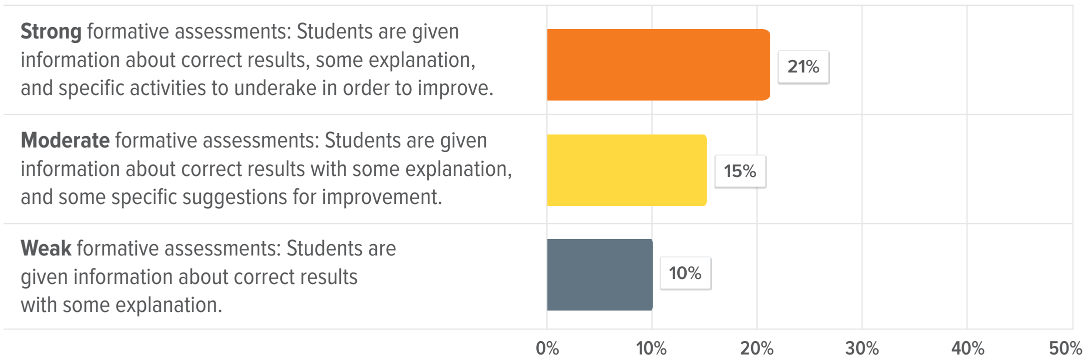
In a recent investigation on the effectiveness of types of feedback, Timmerman and Kruepke found that explanations and remediation were much more effective than simply providing a correct answer.

Nyquist classified formative assessment as strong, moderate, and weak (see Figure 7), supporting the contention that the type of formative assessment provided matters. The strongest type of formative assessment occurred when students were "given information about correct results, some explanation, and specific activities to undertake in order to improve."[27]

With the advent of data-driven decision-making tools and the use of formative assessment increasing numbers of educators are using data to drive instruction. Unfortunately, the feedback that schools offer learners fails to significantly impact learning due to delays in the feedback loops, the lack of specificity, or the non-expert source. As an example of the latter, one researcher found that, in elementary schools, 80 percent of the feedback to learners was from other learners, and 80 percent of that feedback was inaccurate.[28] Overall, researchers have found that in a typical classroom, students receive little if any daily feedback. The use of the intelligent adaptive learning system can change that.

A critical factor in the provision of feedback is the set of conditions under which the feedback is provided to the learner. Feedback is more effective under low-threat, comfortable conditions, which allow the student to pay attention to the feedback.[29] In his meta-analysis of over 800 research studies, researcher Hattie writes, "Students learn most easily in an environment in which they can get and use feedback about what they don't know without fearing negative reactions from their peers or their teacher."[30] Intelligent adaptive learning systems are designed to provide this type of positive feedback.

Figure 7: The Percentile Increase in the Academic Performance of the Average Student when Provided with Weak, Moderate, and Strong Formative Assessments



2. Individualized sequencing of the curriculum and associated learning experiences for each student

Intelligent adaptive learning systems are designed around a modularized curriculum. The sequencing of curriculum units and learning activities within these units significantly influences the depth and efficiency of learning for students. Research from the literature bases of mastery learning, student engagement, and motivation provide support for such adaptivity of the curriculum.

Mastery learning is an early precursor of the intelligent adaptive learning system. It also used a modularized curriculum, but in a rigidly prescribed order, requiring students to work within each curriculum unit or module until they retained an established level of mastery before moving on to the next, again, in the prescribed sequence. This new generation of adaptive learning not only allows a flexible pace through the curriculum; it customizes each student's pathway through the lessons. While some sequencing of lessons is prescribed, in cases where the one is a prerequisite to others, student pathways are generally determined by student readiness and choice. The path is determined in part by the system, based on what a student is ready for, in part to provide a range and diversity of learning experiences to ensure coherent connections and deep understanding, and, in part by the choices the student makes, within parameters established by the system. All such determinations are designed to ensure consistent progressions of learning.[31] This adaptive sequencing of curriculum is supported through research from literature bases on motivation and engagement, prior knowledge, and the theory of flow. Moreover, it enables the presentation of multiple representations of related ideas, thus enabling contextualization of content and processes, ultimately resulting in deeper learning.

Studies indicate that students who are provided choice have higher levels of engagement, which in turn correlates to more time on task and higher achievement.[32] Take for example studies conducted in elementary schools in New Zealand. Research cited in a seminal paper on engagement by Fredricks[33] reported those students who were offered choice as to which tasks to perform and when and where to perform them, "worked strategically and persisted longer in the face of difficulty" than did students in a comparison group.[34] Furthermore, Fredricks reports that student engagement begins to decline as they transition to middle school. That researcher offered an explanation in noting that as elementary students transitioned into middle school the classroom structures became much more rigid, essentially allowing less choice in the learning environment, which may contribute to or accounted for the decline in cognitive engagement after elementary school.[35] Research has also found that the impact of feedback is optimized when there are appropriately challenging tasks, and students are intrinsically motivated to complete such tasks.[36] Student motivation stems from a number of different perceptions and experiences. Students are more motivated to learn when they: 1) feel capable and competent to do what is expected of them, 2) perceive stable links between actions and achievement, 3) have clarity of purpose, and 4) value the subject. Without some degree of motivation, students will not pay attention to the task at hand and such inattention decreases the potential for learning.[37] Experts in cognitive science research have shown how intrinsic motivation of students in learning can be enhanced by building on students' prior knowledge.[38, 39, 40] Making a connection to what interests the student results in a shift from extrinsic to intrinsic motivation, where students focus on their studies because they are motivated by the content itself, with less focus on earning a grade or pleasing teachers or parents.

As described earlier in this paper, keeping a student in his optimized zone of learning requires that the learning activities presented to the student be doable, yet challenging. That requires knowledge of the student's current skill level, and the complexity of task for which he is ready. Too complex a task for the skill level will frustrate the student, and too simple a task for the skill level will bore the student. The intelligent adaptive learning system is able to strike the right balance due to the continuous flow of data from the student actions within the system, something that is difficult for a teacher to do without a technology-based solution such as an intelligent adaptive learning system.

3. The individualized pace of learning

The research basis for competency-based learning, i.e., holding student learning constant and adjusting the time, is grounded in studies of mastery learning. As noted above, mastery learning was an early precursor to intelligent adaptive learning. Typically, both intelligent adaptive learning activities and mastery learning are conducted in a low-stress environment, where the student is allowed sufficient time and provided sufficient instruction and scaffolding to succeed. A researcher who reviewed over 377 studies on mastery learning reported an average moderate effect size of +0.58; that translates into a gain of approximately 22 percentile points for the average learner due to their involvement in mastery learning.[41]

4. The regulation of cognitive load

One of the reasons it is so important to balance the complexity of the task (that is presented to the student) with their current skill level is to avoid learner frustration or boredom (i.e., keep them in their zone of optimal learning).

The culprit that typically causes frustration is cognitive overload—when the material presented is too complex for the student to organize, integrate, synthesize, and understand the concepts contained in the materials. There is a neurological reason for cognitive overload and resultant frustration. Neuroscience research points out the limitation of the human brain in its working memory capacity—the part of the brain used to think. Humans can hold 7 (±2) textual or auditory representations, and 4 (±1) visual representations in working memory.[42] The 7 textual or auditory representations can be single words, phrases, or more complex schemas. The key to avoiding overload is to build the capacity of the learner to incrementally build schemas of understanding of the topic of study. A schema is an underlying organizational pattern, structure, or conceptual framework. Experts studying complex tasks will hold multiple schemas in their working memory in order to solve problems by tapping into the knowledge base from several sources (i.e., schemas) simultaneously. Students involved in deep learning need to do the same.

The importance of avoiding cognitive overload has several implications for the design of intelligent adaptive learning. First, the development of learning activities should use screen real estate to display items that the user might need as background in completing a task in recognition of limited working memory. Second, the learning activities should use a combination of visual and textual, or visual and auditory information in order to leverage the full capacity of the working memory. Visuals can support learners with difficult-to-understand concepts. Visualization and modeling increases conceptual understanding and the likelihood of deep learning and transfer between situations. For example, students who struggle with mathematics often fail to see relationships between mathematics elements. Such representations may take the form of number lines, animations demonstrating concepts, drawings, fraction/number equivalents, virtual manipulatives for exploring mathematical properties, etc. According to the Institute for Educational Sciences, there is moderate evidence for visualization of concepts in mathematics.[43] Third, sound media design principles should be used in screen display to reduce extraneous items, manage cognitive load on working memory, and enhance thinking through sound design. A fourth important consideration is the purposeful development of schemas of understanding by students. This is accomplished through pedagogical approaches that focus on learning with understanding, in addition to ensuring that the student has facilitywith strategies and algorithms for solving problems efficiently and effectively.

5. Student engagement through gaming

Student engagement matters. According to Fredricks, increases in cognitive engagement are directly related to increases in learning. Cognitive engagement is a measure of a student's investment in learning; his thoughtfulness and willingness to exert effort necessary to comprehend complex ideas and master difficult skills.[44] There are a number of instructional and learning strategies that increase student engagement, including: a logical sequencing of curriculum, novelty and variety, student choice, intellectual safety (i.e., system assures the intellectual risks will not be ridiculed), affirmation of the work and progress, and clarity of goals.

Gaming is an example of a learning strategy that embodies several of those listed above. Many intelligent tutoring systems use gaming in ways that appeal to PreK–12 students.

It is ironic that students who find it difficult to concentrate on schoolwork for even short periods of time, often have no difficulty playing computer games for hours at a time. That irony is not lost on educators. According to Gee,[45] educators should apply the principles of game design to increase the depth of learning by improving the quality and timeliness of feedback (i.e., formative assessment), and by increasing learner motivation, attention, and engagement in learning. In fact, there is extensive research underway investigating these tools for educational purposes across a range of grade levels, subject areas, student subgroups, and learning outcomes.[46, 47, 48]

These four reports provide a range of the many emergent studies in this area:

- Simulations and gaming in science. A publication by the National Research Council (NRC) summarized research on games and simulations in the study of science. The NRC found that there was promising evidence that simulations could promote conceptual understanding of science, and moderate evidence that simulations in science increased students' motivation to learn. Though existing studies on gaming in the learning of science seem promising, the NRC noted that the body of literature is too thin to generalize results.
- Online digital content and gaming in preschool literacy. A rigorous study found that integrating digital content from public television video and online games increased early literacy gains significantly in preschool children in comparison to groups of children using more traditional approaches.[49]
- Games and creativity. A study by Michigan State University researchers studied effects of information technology on the creativity of middle school (12-year-old) students. Their results indicated that students who played any type of video game exhibited more creativity than their peers who did not play. The researchers compared students' game playing, Internet use, computer use, and cell phone use, and found that only game playing predicted creativity. Results did not vary by gender or race.[50]
- Psychological Impact. A report by the Pediatric Clinics of North America reported on positive and negative effects of gaming.[51] The positive effects included: 1) action games that improved visual-spatial skills, 2) educational games that teach specific knowledge and skills, 3) exergames that improve physical activity levels, and 4) prosocial games that increase empathy,[52] helping, and possibly reduce aggression.

Meta-analyses from hundreds of studies on gaming indicate that there is, on average, a significant effect on learning, sometimes positive and sometimes negative. The question before researchers is how to leverage the motivational factors into positive results. Studies suggest that the following five principles of effective gaming also serve as important elements of intelligent adaptive learning systems:[53, 54]

1. sequenced challenges
2. "just in time" and "on demand" information
3. performance before competence,
4. motivation and attention
5. timely and specific feedback.

In Summary

The intelligent adaptive learning system should be seen as a diagnostic tool, a learning resource, and a source of valuable data for the teacher, student, and parents. Ultimately, it is the responsibility of the teacher and school to provide a learning environment that uses the latest research based strategies and technologies to enable and optimize student learning. An intelligent adaptive learning system is an extremely important asset in the pedagogical repertoire of the teacher/student team.

As educators make choices about the learning resources they use to advance their students' learning, they use criteria established in their instructional materials selection policies. All learning resources used in a school district, school, or classroom must be vetted. Those criteria should be used when considering intelligent adaptive learning as well. Three of the key criteria are pedagogy, developmental appropriateness, and alignment to standards, in addition to the tenets described in this paper.

Given the promising, emerging research on the potential of intelligent adaptive learning systems to individualize and personalize learning, educators can be optimistic about their potential to improve student achievement. That said, it will be important that the educators vet the resource to ensure pedagogical alignment, and to plan carefully how the intelligent adaptive learning—including the data on student progress—will be integrated into the learning environment.

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j. Shallow learning is memorization, acquiring facts, skills, or methods, typically resulting in a quantitative increase in knowledge. Deep learning is when the student makes sense of the concept, representing that deep understanding by interpreting and applying the concept to a new situation (often referred to as transfer).

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