OBSERVATORY of Educational Innovation Tecnológico de Monterrey

Tecnológico de Monterrey

EduTrends Report

JUL 2014

Adaptive Learning & Testing

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A teaching method that uses a computer system to create a personalized learning experience

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An interactive computer test that efficiently provides questions based on the student's performance level

Introduction: Adaptive Learning & Testing

Adaptive Learning

Adaptive learning became popular in the 70s, when Artificial Intelligence (AI) emerged. Its basic premise was to adapt the learning process to the student's strengths and weaknesses. However, its adoption did not increase at this time due to high costs and the size of computer systems required for a proper implementation.

In a way, adaptive learning personalizes learning techniques, after a differentiating process used to identify the student's specific needs, offering vario us possibilities. This has generated a conceptual confusion between adaptive learning and personalized learning. A common mistake is to use them as synonyms. Hence, it is important to clarify that personalized learning is an "umbrella" which covers different approaches and models, including ability-based learning, differentiated teaching, tutorial models, and also adaptive learning.

From a basic level, personalization goes beyond the "one size fits all" approach; and at a more sophisticated level we find computer guided tutorials. However, personalization in and of by itself does not depend on an adaptability factor. Researchers from Education Growth Advisors (EGA), a strategic consulting firm, define adaptive learning as a method to create a personalized learning experience for students, using a sophisticated computer system based on data. This learning has a non-linear approximation[1] when teaching, providing feedback and correction, because it self-adjusts according to the student's interactions and at his or her proven performance level. Consequently, the system adapts and anticipates the type of content and resources that students will need at a given time to advance through the course.

Figure 1 shows the differences and similarities among differentiated, personalized, and adaptive learning. Differentiated learning is considered a personalization, involving the development of different routes through which students will gain knowledge; while personalized learning includes diagnostics to determine students needs in order to offer a customized solution; in turn, adaptive learning requires incorporating data analyses, psychometric tests, algorithms, among other items, in order to reach learning adaptability, while being a step ahead of students learning.

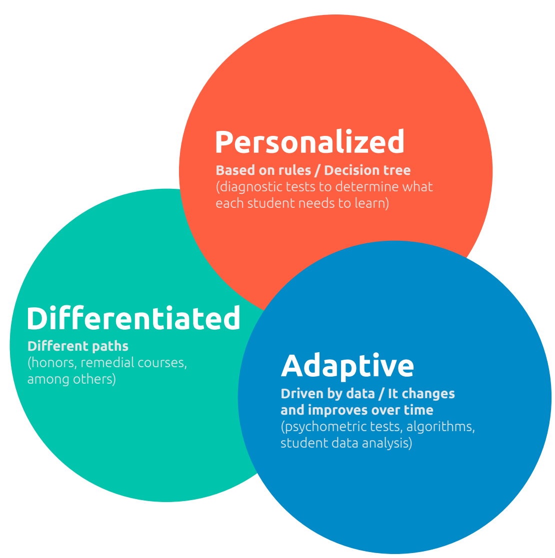


Figure 1. Differences and similarities among personalized, differentiated, and adaptive learning. Adapted from Nepom, 2013.

1 Refers to a learning process that does not involve a pre-established sequence, therefore providing different routes to accomplish anticipated learning

Adaptive Testing

Measuring progress is an important element of an adaptive model, that is, an assessment with adaptive characteristics. Computerized adaptive testing (CAT) was the successor of a series of successful applications emerging in 1905 through the development of Alfred Binet's first adaptive test: *Binet IQ Test*. Adaptive tests are comprised of items or elements selected from a collection (item bank). Elements are selected to match the person's estimated capability (or skill) level: If successful in one element, the next one will be slightly more challenging; in case of failure, the next one will be somewhat less challenging. The test ends when the individual's capability or skill reaches the established objective (Linacre, 2000) or when a certain amount of elements have been presented.

This type of test is made possible by incorporating the Item Response Theory (IRT), a measurement framework used in the design and analysis of educational and psychological assessments. IRT has advantages over the tests' classical theory because it offers a framework allowing testing with different elements in a common scale. This is a significant advantage when multiple evaluation formats need to be related in order for scores to have the same meaning throughout the different evaluations (OAERS, n.d.).

For the purpose of clarifying the difference between adaptive learning and adaptive testing, the figure below depicts the main elements of both trends:

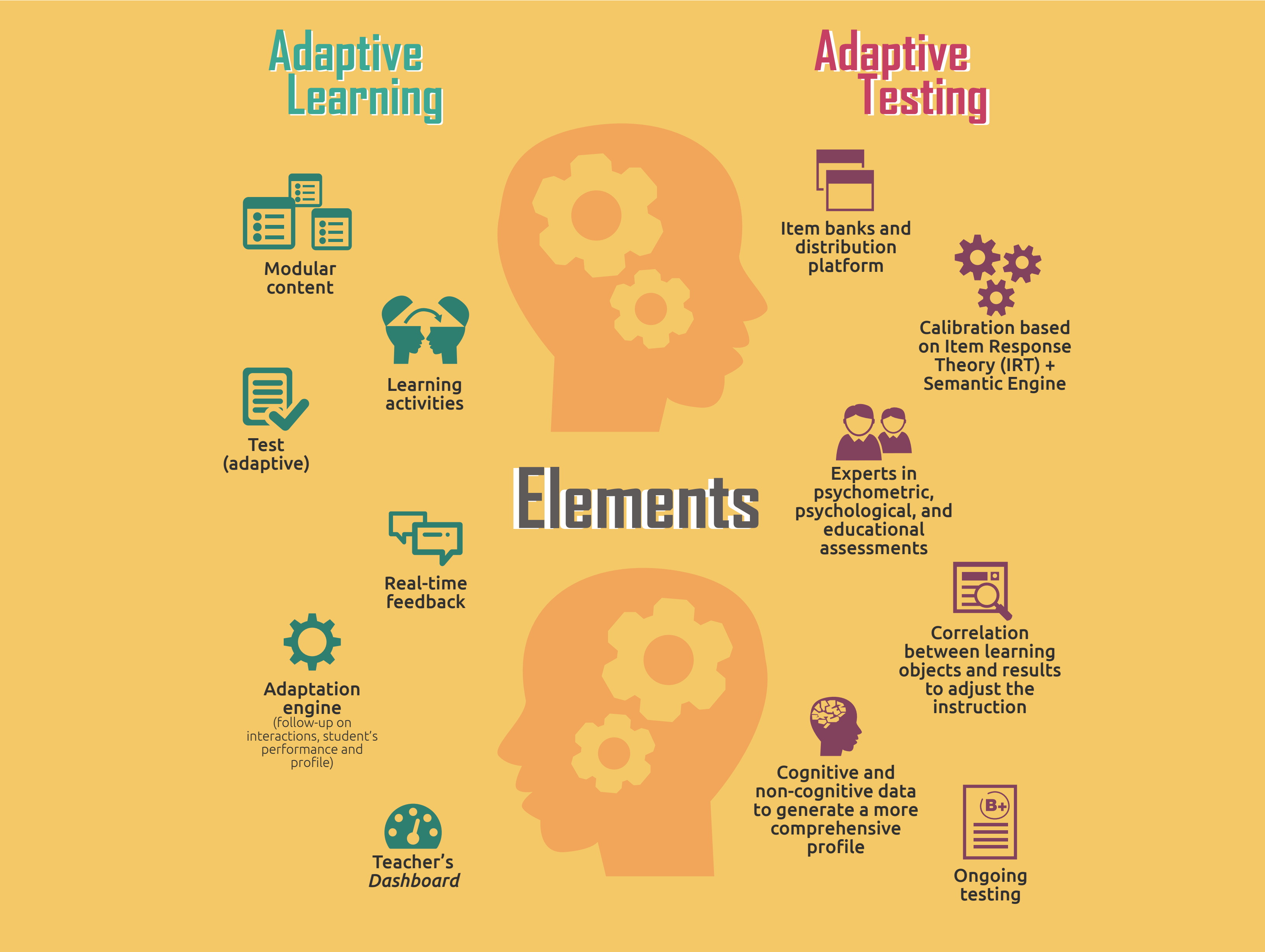


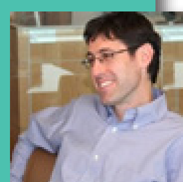
Figure 2. Main elements of adaptive learning and testing.

Adopting the Trend

Adaptive learning is not new. Its inception is generally associated with to *B. F. Skinner's* teaching machine and his Theory of Programmed Learning[2] that emerged in the 50s, and was followed by the Artificial Intelligence movement of the 70s.

With the evolution of Information and Communication Technologies (ICT) and as a result of computers becoming smaller, more powerful and affordable adaptive learning is now applicable to classroom teaching, distance learning, and for tutorials. At present, adaptive learning systems are widely used in different settings to teach and train more efficiently, for example: NASA and several military branches in the United States use it in their programs (DreamBox, 2014); Amazon and Netflix have also adopted this technology to anticipate their client's preferences.

> Technology is not an essential component for personalization, but it is absolutely necessary in order to scale it.
>
> **Adam Newman**
> Founding and Managing Partner of Education Growth Advisors (EGA)



In recent years, adaptive learning has been associated to large-scale data collection. It is deemed as personalized learning with methods of affective computing[3], but just recently we are finally getting to a point where learning adaptability is reachable. This accomplishment has occurred specifically in the education sector where companies like Sherton Software, Carnegie Learning, and Knewton have worked for years developing adaptive learning applications. Knewton in particular, has been able to capitalize upon the concept of adaptive learning by using a platform any institution may purchase. Through its recent partnership with Pearson (one of the world's top publishing houses and educational companies) it is storing large data sets and educational resources enabling them to bring this technology to the masses.

According to the 2012 adopted trends report from Gartner Consulting, adaptive learning was close to the highest peak of inflated expectations. For 2013, the firm placed the trend just barely across the trough of disillusionment. This means, on one hand, that there is a high potential for growth in the following years, and on the other, that we will start to note more and more implementations in the field of education.

MOOC, Big Data, and adaptive learning trends in higher education are considered transformative due to their capacity to offer education in different ways for new students, which will enable the gathering of large quantities of data and may help improve the educational ecosystem (Gartner, 2013).

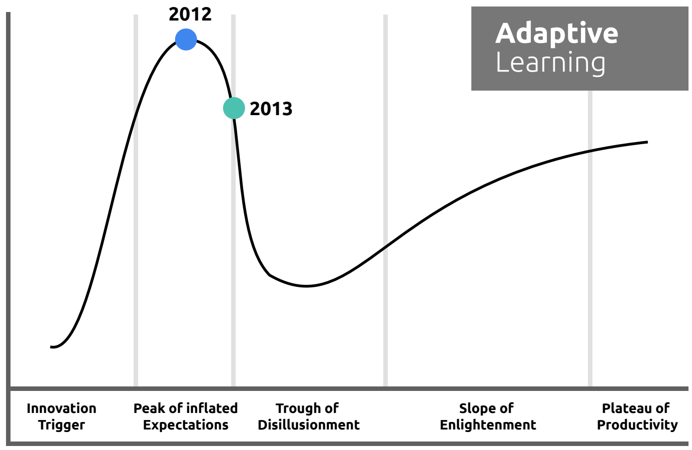


Figure 3. Emerging Technologies Hype Cycle. Hype Cycle for Education. Adapted from Gartner, 2012 and 2013.

We are currently at the eagerly awaited opportunity: for the first time, educators have access to required technology, a sophisticated data and learning analysis, as well as emerging research about how people learn. Convergence of these three elements will lead to intelligent adaptive learning systems (Lemke, 2013, p.6).

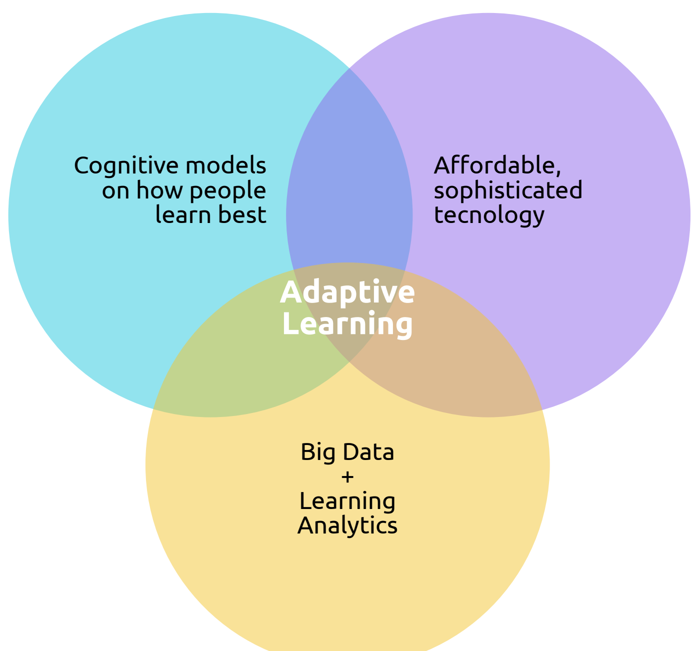


Figure 4. Convergent elements in support of adaptive learning. Adapted from Lemke, 2014.

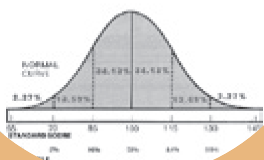
2 The teaching machine mainly comprises a program; a system of combined teaching and testing items that gradually guide students through the knowledge acquired through a response/reward mechanism. Skinner noted that the learning process should be divided into a large number of very small steps and reinforcement must be dependent upon the completion of each step. Skinner suggested the machine in and of itself should not teach, but rather connect students with the person who created its contents. He believed this was the best possible arrangement for learning because it took into account the learning rate of each individual student (Wleklinski, 2011)

3 Emotions are vital in human experience. They influence cognition, perception, and daily tasks such as learning, communication, and decision-making, including rationally (MIT Media Lab, n.d).

ADAPTIVE LEARNING & TESTING

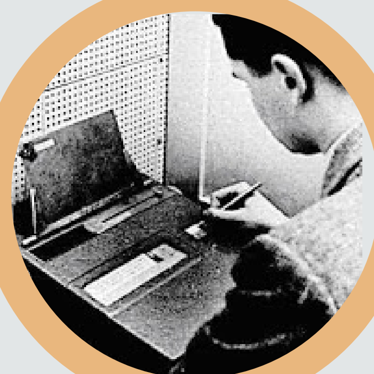
1905

1ST
Adaptive Test
Binet IQ Test
by Alfred Binet



1950

Skinner's machine



1959

PLATO

Programmed Logic for Automated Teaching Operations
System developed at the University of Illinois

1970

SCHOLAR

Firts intelligent tutorial system created by Jaime Carbonell

CAI

Computer Aided Instruction

1980

LOGO
Programming language

Computer Based Testing

1988

Université de Montréal

University of Montreal organizes the first **INTERNATIONAL CONFERENCE ON ITS** (Intelligent Tutoring Systems)

1990

Computer Assisted Instruction

1993

AiED

1st INTERNACIONAL CONFERENCE ON ARTIFICIAL INTELLIGENCE IN EDUCATION (*AiED*).
Edinburgh
United kingdom

1998

Carnegie Learning

2000

LMS
LEARNING MANAGEMENT SYSTEM

2006

ADAPTIVE TUTORIALS
Graphic Simulators

2008

KNEWTON

2009

MOST POPULAR PLATFORMS

LearnSmart

MindTap
Personal Learning Experience

KNEWTON

Grockit

2010

SMART SPARROW

2011

MOOC

2012

Gartner
EMERGING TRENDS
Adaptive learning reaches its highest peak of expectations

2014

Adaptive learning models

Providers offering adaptive learning solutions usually work in different academic research areas, including intelligent tutoring systems, automated learning, memory and cognitive theories, among others. In addition, adaptive learning systems have been generally divided into categories or models under different names. Regardless of these variations, it is clear there are two general models that are not mutually exclusive. This idea is also supported by researchers from EGA (2013b, pp. 5-6):

- **Content driven.** This model is based on monitoring performance, interactions, and metadata generated by the interaction between students and content. This information and its relation to the learning objectives is gathered on a dashboard used by the professor to identify what adjustments or changes are necessary for teaching, contents or paths.
- **Test driven.** This is the model commonly associated to adaptive learning. In this approach, the system makes, almost in real time and dynamically, any adjustments in teaching, learning resources, and course paths, based on continuous testing of the learner's performance and command. The professor's intervention is not necessary.

To illustrate the first model we can highlight Cheryl Lemke's (2013) case, President and CEO of the Metiri Group, who developed a content-driven model known as intelligent adaptive learning. She defines it as digital learning that immerses students in a modular learning environment where each decision is entered and then used to guide their learning experiences and adjust the path and pacing of the lectures. This provides formative and summative information for the professors (p. 2). This model adapts the instruction to each student's particular needs, current knowledge, and interests.

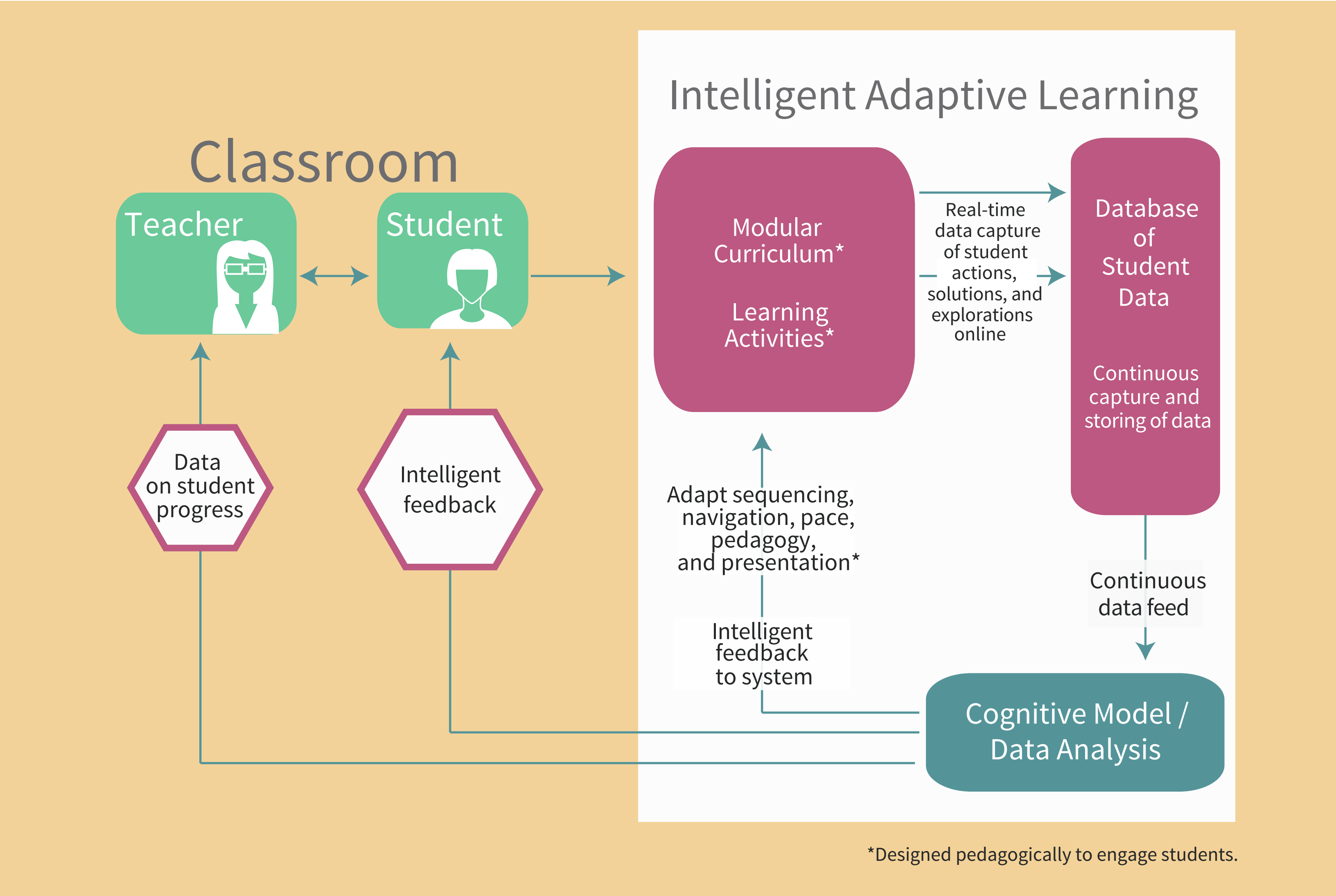


Figure 5. Intelligent adaptive learning model. Adapted from Lemke, 2014.

Test-driven models are based on computerized adaptive systems, according to Kinsbury, Freeman, and Nesterak (2013). These are characterized by having a basic structure and procedures: A pool of questions from where these are selected, a calibration in a common measurement scale, a question selection mechanism based on student responses, a response assessment process, a process to end the test, and a relation report between students' scores and needs.

Adaptive tests are a fundamental aspect of these models. These comprise two basic steps: Question selection and score estimation (Davey, 2011). The first step determines the most appropriate question or collection of questions given the student's performance level. The second step uses the responses to the questions previously answered in order to estimate student's performance, which renders the following questions more appropriate.

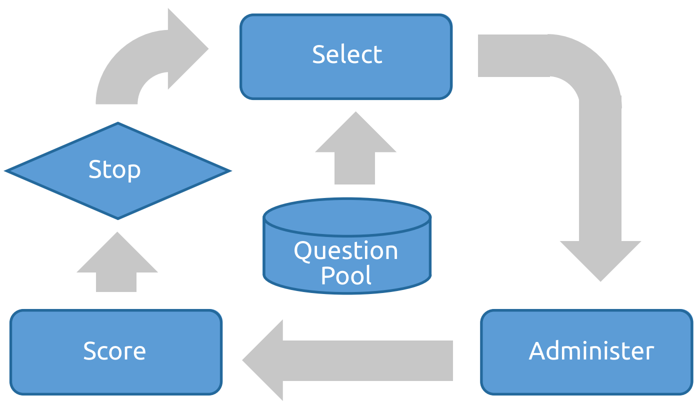


Figure 6. The adaptive testing cycle. Adapted from Davey, 2011.

Question selection can be done at various levels of *Multistage Testing* (MST), which starts by administering to each student a moderately difficult bundle of items called a routing test, and depending on their performance, students are assigned questions within a wide range of difficulty levels.

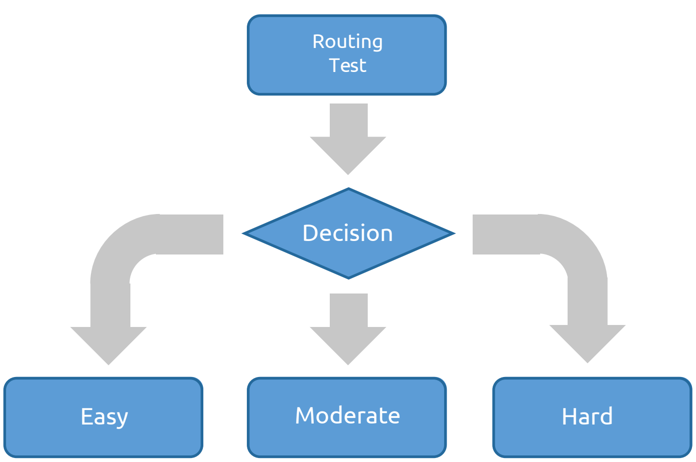


Figure 7. A two-stage Multistage Testing. Adapted from Davey, 2011.

Figures 6 and 7 depict the process flows of a test-driven adaptive learning model. This is developed as a cycle, ending when a certain level of score accuracy is attained, or when a certain number of questions have been presented.

Adaptive Learning and Testing Systems

There are several adaptive learning applications that range from basic, such as audience response systems (*clickers*) –allowing the speaker to adjust his presentation in real time based on feedback received from his audience–, up to more sophisticated systems that adjust the type of questions given to students depending on their previous answers, as in the case of the computer-based TOEFL.

Currently, the most relevant systems in education are the following:

Adaptive tests (computer-based):

Based on Computerized Adaptive Testing (CAT), these tests are built around complex algorithms to adapt and produce optimum tests for each student (FastTest, 2013). The test focuses on providing items that are most appropriate for an individual's level. FastTest states that these tests provide the following benefits:

- Shorter tests (50 to 90 percent time reduction)
- More accurate scores
- Increased personal motivation
- Greater test reliability

Adaptive tutorials:

These are Intelligent Tutoring Systems (ITS)[4] in which students interact by means of a task-objective simulation while being guided and remediated. Adaptive tutorials can exhibit different types of feedback for students and teacher. Students receive guidance based on their interaction, while teachers receive feedback according to their own authoring choices to boost reflection and content adaptation (Marcus, Ben-Naim, and Bain, 2011, p.626).

Adaptive tutorials are designed to enable teachers to monitor overall answers of large groups of students, and to adjust the teaching and feedback provided by the tutorials and respond to common sticking points. By analyzing student feedback and performance in assessment tasks, we can see how tutorials engage students in working through conceptual difficulties

4 The first ITS, SCHOLAR, was developed by Jaime Carbonell in 1969 to teach Latin American geography (Junghyun, n.d.).

(Prusty, Russel, Ford, Ben-Naim, Ho, Vrcelj, and Marcus, 2011, p.2). In these systems, adaptation occurs at three levels:

- **Feedback:** From activities, responses, test results, and errors.
- **Sequence of activities:** Dynamically based on students' performance.
- **Reflection (from teachers):** In accordance to student needs and performance.

Cognitive (intelligent) tutors:

These are a particular type of ITS using Artificial Intelligence to simulate the behavior of a human tutor. To do so, they are based on AI research, a branch still under development. Intelligent tutors provide exercises until the subject is mastered; after that, they offer personalized instruction and feedback allowing students to learn at their own pace. And lastly, they gather detailed data enabling instructors to monitor, and intervene in the learning process, if necessary.

PLATFORMS

Figure 8. Platforms offering adaptive learning and testing solutions in K12 and HE.

Relevace for Tecnológico de Monterrey

For Tecnológico de Monterrey, learning personalization has always been an important element within its objectives. In the last four decades, several models and systems have been explored and tested since the Personalized Instruction System (SIP) appeared in Brasilia in 1963, the largest number of SIP courses implemented in a single institution was at Tecnológico de Monterrey (Díaz, 1976).

Adaptive learning and testing have the potential to further improve the learning experience, as well as motivate and engage students, to personalize paths within courses and syllabi, and allow teachers to use lecture time more productively. Also, they can contribute significantly to promote student retention, to assess their knowledge, and to improve their academic performance[5]. It will enable our students to be better prepared for their professional success.

With the new TEC21 educational model, Tecnológico de Monterrey will foster the implementation of adaptive learning and testing. As David Garza -Vice Dean of Undergraduate Studies- has mentioned, new syllabi will implement adaptive testing in the first phase, and will incorporate Mastery Learning in remedial courses. This will directly support the model's objectives: Flexibility, and challenging and interactive learning experiences.

Adaptive learning will develop better cognitive skills in our students and increased academic productivity through activities bearing a quantifiable impact and higher value.

Omar Olmos
Basic Science Department Chair
Tecnológico de Monterrey, Toluca Campus

It is important to emphasize that Mastery Learning is a pedagogy that adequately incorporates into adaptive learning and testing. Based on Bloom's Taxonomy model (1968), each student is individually given the amount and type of instruction necessary to reach higher or complete level of achievement, and balanced performance from all students (Kulik, Kulik, and Bangert-Drowns, 1990). It also offers benefits such as: ensuring that the ultimate goal of the course is achieved, are understood and learned, providing clear and personalized feedback to each student, and supporting students of outstanding performance to develop their full potential through new activities (Mazarin, 2014).

On the other hand, adaptive systems can be used in hybrid learning environments to accomplish a better personalization, allowing students to track their own learning. This develops self-control and participatory skills in the personal learning process (DreamBox Learning, 2014). Combining adaptive learning programs with an hybrid model can also enhance the instructional design teachers use to interact with students one-on-one.

Adaptive learning and testing platforms constantly monitor and analyze responses, and this information enables the teacher to identify more precisely whether students are understanding the materials or not, in order to offer guidance to those who may need it (Kerns, 2013). Moreover, it allows a right balance between online contents and classroom activities, freeing up enough time to go into more advanced concepts in greater depth, and participate in higher-level discussions. Thus, the professor has a more active role as facilitator or mentor (Carter, 2014).

Likewise, adaptive learning and testing can further enhance the learning experience through teacher-student interaction, because it provides immediate feedback to both parties about student strengths and weaknesses, focusing on particular needs. Furthermore, if offers the following benefits from the student's perspective (CTU, 2013):

- **Increased control over their learning:** When confronting challenges and problems that match their level of understanding and progress on a particular topic, students can move quickly through an area of mastery and then address the areas they need to improve upon.
- **Improved results:** Students can perform better because adaptive learning offers additional support in the areas they find most challenging.
- **Higher confidence:** Students feel a stronger sense of confidence as they proactively address learning gaps.

5 There are numerous case studies and success stories regarding the effectiveness of adaptive learning that have demonstrated an increase in scores (between 10 and 15 percent), as well as graduation rates (between 17 and 20 percent). In parallel, institutions that have implemented adaptive learning or testing systems of some sort have also increased their student retention percentage. Ranges obtained by considering success stories documented on Knewton, Learn Smart, and Carnegie Learning websites

Adaptive Learning & Testing **Benefits**

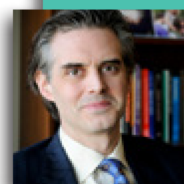
Figure 9. Adaptive Learning and Testing Benefits.

According to Christina Yu (2014), adaptive systems allow students to have a higher mastery in their academic progress by following the next four actions:

- **Through errors.** A fundamental element to improve learning. Errors are the main element adaptive systems grade to establish a learning path that is appropriate to students needs and the instruction they require. It is the most valuable element in this process. The purpose is to dynamically designe and adapt the learning path according to students improvements at each stage.
- **Through rapid feedback.** For trying, failing, and trying again. Providing real time feedback can reduce the anxiety associated with school performance and promote iterative testing. Thus, the learning process focuses on exploration and knowledge development in the long term, rather than on a test-based score.

- **By focusing on student needs.** Providing specific information to enhance student skills or competences, solving recurring questions, offering support with learning “gaps”, and giving effective feedback, to develop in the student a perception of their own capabilities and values of hard work and perseverance. Moreover, this encourages the development of an intrinsic motivation.
- **With reflection and self-awareness.** Students will be able to recognize patterns within their own learning processes: Their most frequent errors, study habits that have worked for them, the types of challenges they like the most, among others, in order to increase them or amend them. Adaptive systems can generate reports to identify those patters, in order to provide support the leaving process of students and obtaining better results.

In practice, the value of adaptive learning and testing lies in the data incorporated into each learning object to identify its relevance for students when understanding and mastering a topic. Tangible benefits can be obtained from a large amount of information generated by educational institutions (Gartner, 2013). The Tecnológico de Monterrey is one of the few universities in the world with enough students enrolled to reach critical mass in data collection, so they are statistically relevant (one of the great challenges of implementing adaptive learning). Data management and analysis will help generate predictive tools that teachers can use to improve the individual learning of each student, creating new mechanisms to follow-up and adapt to their needs, impossible with traditional methods.



By integrating online platforms we are able to experience personalized learning, and by using Big Data we may see activities carried out and results per student or per class; this is why adaptive learning is the future of higher education.

Doug Guthrie

George Washington University Professor

Adaptive Learning & Testing
in Tecnológico de Monterrey

There are various adaptive learning and testing initiatives at Tecnológico de Monterrey. The following list includes works, experiences, and efforts from professors tackling this subject.

Adaptive Learning Projects

SI-APRENDE

Julieta Noguez, Liliana Argotte, Gustavo Arroyo and Luis Neri
Mexico City Campus

The Intelligent System SI-APRENDE uses a tutorial model drawing from an Intelligent Tutoring System (ITS) model to set up an adaptive sequence and navigation of learning elements, under the SCORM standard.

The ITS model is based on dynamic decision networks in order to select the pedagogical action which better adapts to each student's learning situation. It was developed in collaboration with the Electrical Research Institute as part of a master's thesis project.

SiEntrenO

Julieta Noguez, Luis Neri and Daniel Blancas
Mexico City Campus

It consists of an Intelligent Tutoring System (ITS) used to train new operators at a combined cycle power plant. It uses 3D simulations to visualize the plant's circuit where the operator is practicing. The course is available in an integrated web environment that facilitates managing users and tracking operators' performance.

What makes learning easier is the modeling and simplification of complex concepts in thermodynamics governing the operation of a combined cycle power plant. Furthermore, it includes online dynamic experiments and simulations carefully designed with meta variables, restriction variables, exploration variables, as well as dynamic variables.

The system is able to infer, through bayesian and decision networks, the knowledge gained by the operator in terms of the interaction with simulations in order to provide feedback, help, content, and new experiments.

Adaptive Learning in Math Courses

Patricia Salinas
Monterrey Campus

The implementation of the teaching method consists of experimenting with three adaptive learning platforms in math courses: Cognitive Tutor, Knewton, and Aleks.

Cognitive Tutor works as a controlled guide throughout the student's processes when working on an activity: It guides the student to respond questions correctly, or inviting him/her to rectify the answer, specifying what he/she needs to do in every step. Knewton shows short videos where teachers explain the procedure to follow, and offers feedback for each response: Exercises provide context for each problem and not only focus on solving the equation. Lastly, Aleks allows teachers to previously add completed solutions, which the student will receive when needed.

All three platforms guide the student step by step through a path, and although it is different for each student, it follows the same contents.

AdaptaTEC21

Raúl Crespo and Lourdes Muñoz
Mexico City and Santa Fe Campus

The purpose of this project is to research how to implement adaptive learning throughout different disciplines such as engineering, humanities, and business at the high school and in higher education levels. AdaptaTEC21 is currently selecting the most appropriate topics and subjects for the pilot to be tested in the 2014 fall semester. The hypothesis to be tested in this initiative is if the student's learning will be more meaningful and personalized when combinig classroom activities with activities in an adaptive platform.

Selective hybrid

Juan Carlos Altamirano and Guillermo Dunckel
Guadalajara Campus

This is a series of pilot programs with flexible hybrid courses, adaptable to curricular needs and customizable to the requirements of each participant, in order to enrich the teaching-learning experience. The project has the objective to cover the need for an homogeneous and comprehensive competency-based test, leveraging facilities and human resources. To do so, a technological platform is employed with subjects, educational materials, resources, and all types of materials, which allows testing regardless of the students' location.

Intelligent Interactive Adaptive Tutorials

Rubén Darío Santiago and Francisco Delgado
Estado de Mexico Campus

This project proposed the development of a course on the first three levels of Bloom's Taxonomy, using typical exercises that generate a personalized learning path. The student makes progress according to proven capabilities, because if he/she does not show the necessary abilities, he/she will not be allowed to continue until an acceptable proficiency has been reached.

Adaptive Testing Projects

Aaprender

Julieta Noguez
Mexico City Campus

This project proposes the development of an online adaptive learning tool called Aaprender. This tool is a system in which each student follows a different sequence of exercises depending on their interaction with the system, and provides feedback to students. If the option selected is correct, the system provides either a more challenging question or the next exercise in the list; if the option selected is incorrect, the system provides a similar exercise but easier, in order to remedy that particular issue. Also, teachers can create specific reports about the students' performance and class in general.

TecEval

Gerardo Aguilar
Mexico City Campus

It is an online dynamic testing system, accessible from a computer or mobile device, for math and physics courses, with the possibility of using it for other subjects. It enables posing dynamic (algorithmic) and open questions, facilitating writing math symbols and determining the automatic score of the different types of questions. Additionally, this system provides statistical follow-up of the students and is incorporated into Newton GymLab.

Linear Algebra Course

Eduardo Uresti
Monterrey Campus

It involves creating a bank of more than 900 items distributed throughout the course. The database was debugged during several semesters, obtaining psychometric indicators used to determine the level of difficulty and differentiate the ones further away from the test's objective, with the purpose of gaining reliable results from the items. Educational materials have also been prepared for all subjects in the course.

Currently there is a system under development, which will establish a relation between the evaluation of students and corresponding educational materials in order to perform personalized evaluations.

Personalized Learning Projects

SSEA System

Omar Olmos
Toluca Campus

This information system allows concentrating performance results for each class, showing students, teachers, and directors relevant information about the students' academic performance, as well as the quality of service offered by the professor in each course.

Currently, at the Toluca Campus, there are close to 200 courses taught in basic subjects at high school and higher education levels. This system has been adopted by the Veracruz, Obregón, Cuernavaca, Guadalajara, Hidalgo, and Santa Fe Campuses. As a result of using this tool, students have been able to increase their approval percentage in standardized CENEVAL (EXIL) tests from 65% to 95% in Physics and Math during the first third of their college education

WAVE Tests and Doctoral Student Visits

Graduate Area
EGADE Business School

EGADE Business School applies WAVE tests to all students in order to detect their competences, and based on these results, generates a series of workshops offering students the continued development of those skills.

Doctorate studies at the EGADE Business School and other national institutions are custom-designed for each student, who will carry out specific research visits to develop skills in his/her discipline.

Personal Pace

Gabriela Vázquez
Guadalajara Campus

At the Guadalajara Campus, by adapting to students profiles, new ways to accredit courses are under research. It is intended to implement the project at every Tecnológico de Monterrey course, so far, however, it is only focused on remedial math. The methodology being used is breaking the course into modules. In order to place students into a module, they must take a placement test. The first implementation will take place in July 2014.

Tec Student DNA

Angélica Ibarra Aoki and Sergio Sánchez
Guadalajara Campus

This project's objective is to define the variables which allow learning, explaining, and adapting teaching-learning processes, attained through data collection of learning styles, psychometric tests, curricula, academic performance, and students' abilities profiles. The platform will generate indicators and boards to let deans, directors, professors, and tutors identify risk factors in the success of students, in addition to formulating the appropriate assurance measures.

This platform aims to ensure students graduate with the profile stated in the institution's mission. The first phase of the project included a prototype drawn from existing databases. In the second phase, databases will be generated from information not yet collected.

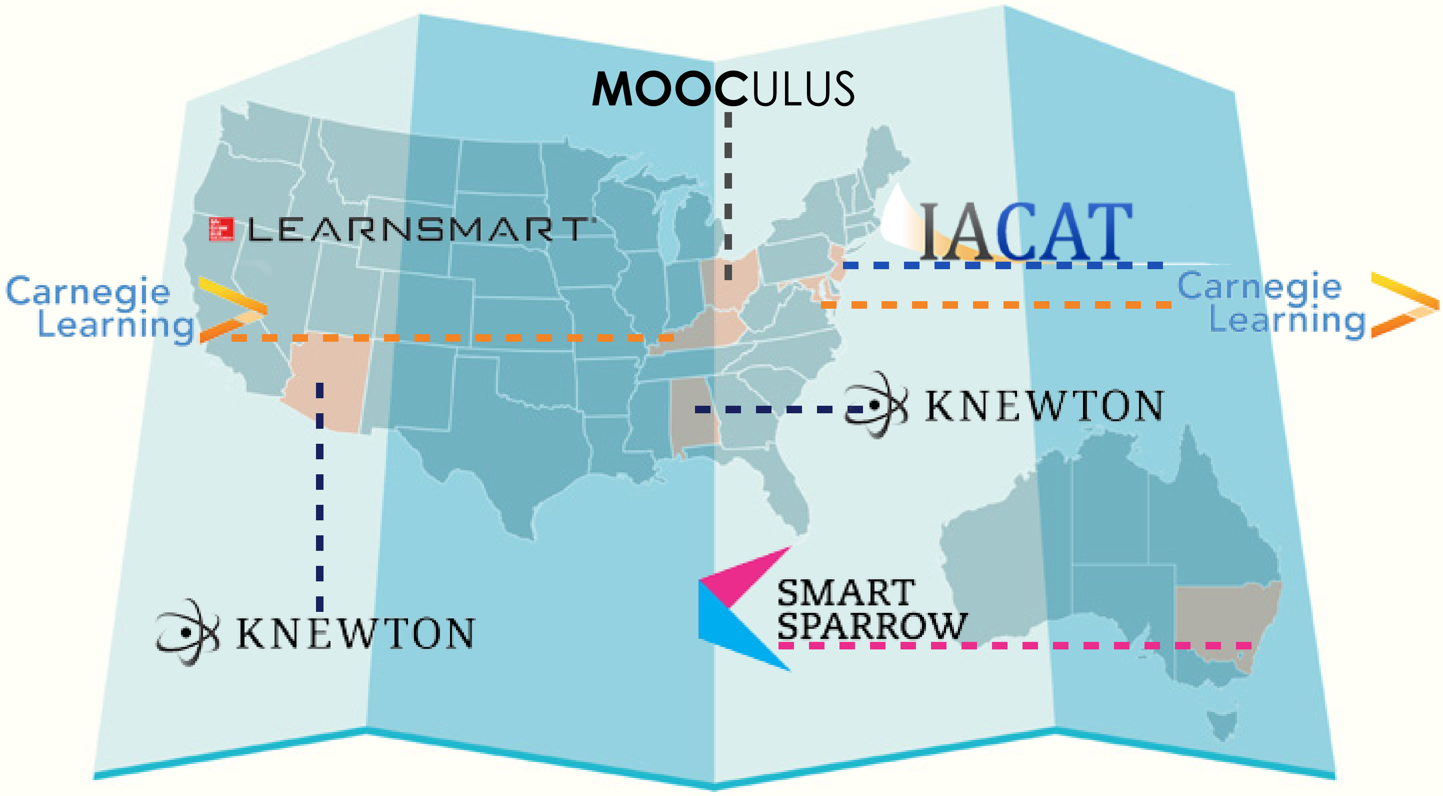
Learning Analytics

Julieta Noguez and Omar Olmos
Mexico City and Toluca Campus

Learning Analytics is a collaborative project between professors from Mexico City and Toluca campuses, who seek to join efforts carried out in recent years regarding the development of adaptive learning systems and information systems in real time. The idea is to choose appropriate pedagogical actions, first through an educational model supported by TIC, as well as predictive models allowing the implementation of adaptive processes with support from data analysis to detect critical factors in desertion of students.

The end goal is for both students and faculty to interact with each other, and have a positive impact on student's learning.

What Are Other Institutions Doing?



Improved performance in math courses

Decreased desertion rates

2002-2004

Dundalk High School (in Maryland) showed an increase from 49% to 86% in students passing math by using Cognitive Tutor Software from Carnegie Learning (Carnegie Learning, 2004).

2009

Kentucky's West High School District achieved the best scores in math by using Cognitive Tutor Software from Carnegie Learning (Murrin, 2009).

2010

The New South Wales University applied online adaptive tutoring using the Smart Sparrow platform for the first year of Mechanical Engineering studies, decreasing its desertion rates to 31%.

2011

- Arizona State University (ASU) redesigned math courses with support from the Knewton platform. Preliminary results from this study showed an 18% increase in the number of students with passing grades. Also, retention percentage increased by 47%. The university estimates that so far, 12 million dollars have been retained that otherwise would have been lost due to student desertion (EGA, 2013a, p.11).

- Furthermore, the university partnered with Pearson to implement the Knewton system on its courses –online and hybrid–. Pearson provided the educational content and Knewton provided the algorithms and platform (Kolowich, 2013a).

2012

- The University of Alabama (UA) used Knewton in their remedial math class and obtained results in the percentage of passing students: It demonstrated an increase from 70% to 87% in the first semester (Knewton, 2012).

- Jim Fowler and Thomas Evans, professors at Ohio State University, created a MOOC (Calculus One) to teach calculus, using adaptive testing. To do so, they developed the MOOCulus tool to complement Coursera's platform.

2013

- Different technical and state universities in the United States used the LearnSmart platform from McGraw-Hill. They increased their student's performance from 10% to 15% and, in some cases, a 17-20% [6] increase in retention.

2014

- The International Association for Computerized Adaptive Testing (IACAT) will hold the Computerized Adaptive Testing Summit in Princeton from October 8th through the 10th. This event will be hosted by the Educational Testing Service (ETS), on the topic of "Facing and Solving Educational and Psychological Measurement Challenges in the 21st Century."

6 Information gathered from case studies and LearnSmart efficiency.

Where Is This Trend Headed?

In 2014, The Chronicle of Higher Education conducted a survey completed by some 350 presidents of different universities which focused on the trends they considered more relevant for higher education in the United States. The results show hybrid courses (combined online and classroom education) and adaptive learning will have a strong positive influence in higher education in the future.

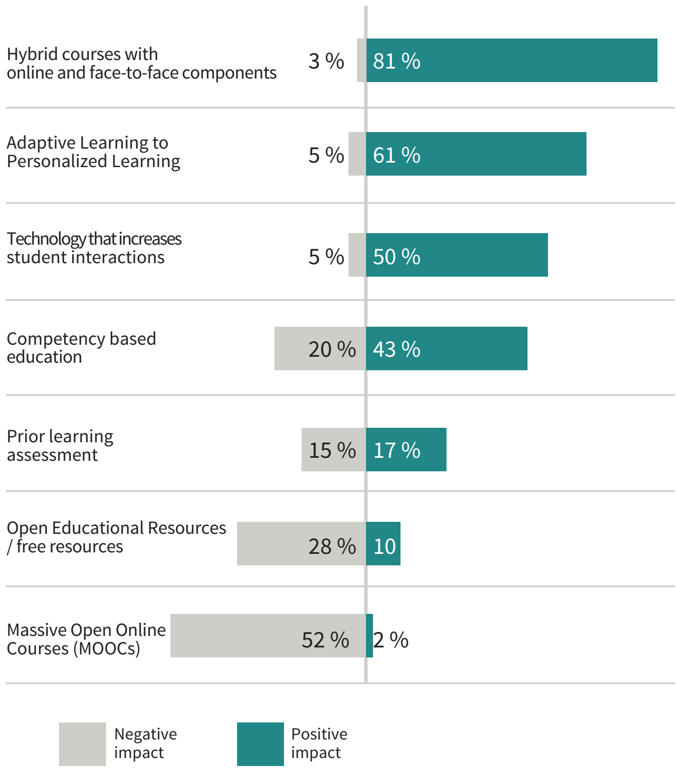


Figure 10. Predictions about which innovations will have the most positive or negative impact on higher education in the future (in the United States). Adapted from The Innovative University: What College Presidents Think About Change in American Higher Education. The Chronicle of Higher Education, 2013.

On one hand, integrating adaptive learning into MOOC will allow teachers to measure understanding of the topics in real time, and adjust the material presented to students depending on their needs to reach their highest levels (Kolowich, 2013b). Furthermore, the degree of personalization provided by adaptive learning systems will create a professional training model [continuing education] much more efficient at mass scale (Nielson, 2014). More experimentation such as the one carried out by Ohio State University with MOOC Calculus One using adaptive testing (MOOCulus tool) is expected.

On the other hand, educational institutions are beginning to analyze the integration between adaptive learning and learning analytics. This will enable the professor to have information about his/her student's performance in other courses, identify learning problems and address them in a timely manner, learn about the effectiveness of a particular course or program, and identify the areas to improve, personalize his/her courses, discover trends and patterns in student behavior, among other advantages (NMC, 2014).

In adaptive learning there are two main trends: Learning analytics to adapt educational strategies and instructional design, and intelligent models to infer the student's cognitive status to provide the contents, activities, and tests depending on his/her interaction and way of learning.

Julieta Noguez
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Implementing adaptive learning into courses may also facilitate adding other educational trends. For example, gamification elements could be included in a transparent manner, such as: progress bars, badges, results tracker, connection with social media, stories or metaphores, among others, thus potentially increasing motivation and engagement while suggesting challenging learning experiences, and increasing the student's performance. When adaptive learning adjusts instruction and testing according to the student's needs, it increases their confidence, balancing what the student knows at that moment with what he/she can achieve. In turn, as the student progresses he/she develops skills and reaches goals supported by feedback and the instructional design received from the teacher.

On its own, Big Data is adopting an increasingly prominent role in universities' decision-making processes, since data banks analyses can identify patterns and complex relationships, accurately demonstrating the effectiveness of educational models. For example: Through the use of Big Data, along with adaptive learning tools, we can identify which sections of a book are most difficult to grasp or which are more effective in conveying concepts. When having a large amount of data about searches, results, response times, percentage of progress in each paragraph of a book, it is possible to have a more clear and punctual image about which content is efficient in conveying concepts; which still needs to be finessed, and which are the sections students are struggling with (Feldman, 2014).

Major educational publishers such as Pearson, McGraw-Hill, Wiley & Sons, and Cengage Learning have long been transposing their textbook content onto dynamic online platforms equipped with the necessary tools to collect data from students using its contents. Vendors such as Blackboard and Ellucian have invested in analytics tools that aim to predict student success based on data logged by their systems. And the Bill & Melinda Gates Foundation has marshaled its outsize influence in higher education to promote the use of data to measure and improve student learning outcomes, both online and in traditional classrooms (Kolowich, 2013).

A Critical Glance

There are two key challenges in implementing adaptive learning. The first one is obtaining statistically valid data sets in order to provide personalized learning advice to students, considering the preparation involved for the teachers or experts who will prepare the contents, in addition to the corresponding instructional design. On the other hand, the second challenge is the increasing number of vendors. This could lead to some confusion, negatively impacting students when transitioning from the different adaptive learning platforms.

It is very important to bring to the table the issue of Metadata standardization in collecting the big data sets required to provide a transparent transition between current platforms and those which may arise. It is also necessary to take into account how students' privacy laws and their rejection to tracking their interactions will have an impact on gathering the information. Lastly, we still need to demonstrate that adaptive learning platforms work with any topic, not only those relatively structured, as in the area of mathematics (Gartner, 2013).

Figure 11. Main challenges faced by adaptive learning.

Learning 1:1 vs. Collaborative Learning

Dan Meyer, PhD student in education at Stanford University and renowned speaker, launched a provocative but interesting criticism regarding adaptive learning in May, 2014: Adaptive Learning Is An Infinite iPod That Only Plays Neil Diamond. For Meyer, a computerized adaptive learning model leaves behind the social aspects of learning that rise from the interaction between students, interactions that can't be individualized or self-paced. Lectures and fluency in procedures are an important aspect of a student's mathematics education, but they are only one element in the universe of experiences in Mathematics.

> We should make good use of the presence in the classroom to do something technology can't provide... different approaches or methods, challenging activities, collaboration... that is, finding a way for students to develop a passionate interest toward scientific knowledge.

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In response to this criticism primarily centered on technology, Tim Hudson, curricular design director at DreamBox Learning, mentioned that adaptability already exists and has been present in classrooms. Without adaptability elements, classrooms, applications, and software couldn't really be efficient for learning or receiving feedback. However, adaptability (in people and computers) will not mean much if students' tasks are narrow and shallow or if problems do not invite them to use their own ideas in order for their mistakes to drive a deeper understanding of concepts. The software can't and shouldn't try to do everything, students must collaborate among themselves in enriching tasks. Still, well-designed software can support student's learning and complement their classroom experiences in a way that would not be possible without digital technology.

What can computers assess?

One of the promises of computer-aided instruction is that each student receives what he/she needs because the computer can quickly learn what the student knows or doesn't know. The computer can assess him/her instantly and constantly, and based on this, supply the appropriate content more dynamically, a teacher definitely does not have enough time to do this.

Justin Reich (2014), in his article Computers Can Assess What Computers Do Best, analyzed computer assessments and where this trend is going. Overall, computers (without human training) are good at assessing quantitative things, computational things, things that computers are good at doing. This is to say that they are good at assessing things that we no longer need humans to do anymore. Operating as support and not as complement.

Computers can efficiently assess the following:

- Multiple-choice questions
- Quantitative questions with a single right answer
- Computer code
- Standardized essays of about 400 words (with some help from humans)

This computer assessment question is really the vital factor of blended learning models and for models that depend upon software to assess and teach students. Reich concludes that as long as we face these limits on what computers can assess, we'll face serious limits on the fields where computers can supplement or replace teachers. The fields in which computer assessment falls short may prove to be the most important fields for student learning.

Designed based on behavior profiles

Audrey Watters (2012) described any company touting adaptive learning software as being influenced heavily –if not entirely– by the behaviorist B.F. Skinner. The Skinner approach is used by many adaptive platform developers because collecting and interpreting data is based on the student's (or consumer's) behavior. However, we know that Skinner's ideas do not match the research about how humans develop cognitively.

On the other hand, Tim Hudson (2012) explains that despite the adaptive learning developer's noble goals, the design of each adaptive platform reveals important pedagogical approaches and assumptions made by the developers. If we analyze an adaptive platform design we can determine the pedagogy and the way students engage students with learning.

Hudson (2012), in his article "Adaptive" Learning Technologies: Pedagogy Should Drive Platform summarizes the weaknesses of an adaptive platform designed solely based on behavior profiles:

- It replicates many of the mistakes of Individually Prescribed Instruction (IPI), most notably the flawed assumption that "learning comes about by the accretion of little bits" (Shepard in Hudson, 2012).

- These platforms are dependent on a pedagogical model where the teacher (or system) “delivers” content and students become “receivers” of information. The lessons and instruction are static, and students therefore never engage in authentic, independent thinking.
- Data collected (although plenty) are not about students’ understanding and cognitive development, they are about behaviors and the ability to replicate procedures on shallow assessment items.
- The “adaptability” for students not making progress is essentially recommending that they passively receive the same or similar static content again.

While this ‘behavioral profile’ platform design is effective for making entertainment recommendations (Netflix), it has several weaknesses and limitations when applied directly to learning.

Tim Hudson
Curricular Design Director at DreamBox Learning

Recommended Actions

Recommendations by the Observatory of Educational Innovation that allow to explore the potential of adaptive learning and testing

- Analyze the subject or contents you teach, identify which contents can be applied using adaptive learning or testing
- Apply questionnaires on study habits, multiple intelligences or learning styles that may provide more information about your students
- Analyze the available platforms (use the information provided in this report)
- Talk to your department about the possibility of launching a pilot program
- If your institution already carries adaptive learning or testing projects, join in the collaboration. If you have already developed a project, share your experience with your colleagues
- Contact the department in charge of Educational Technologies in your institution to analyze how to provide these adaptive tools

Professor of the Tecnológico de Monterrey:
Join the innovative community

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