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Using Learning Analytics to Improve Students' Reading Skills: A Case Study in an American International School with English as an Additional Language (EAL) Students[1]

Uso de Analíticas de Aprendizaje para Mejorar las Habilidades Lectoras de Estudiantes: Un Estudio de Caso en un Colegio Americano Internacional con Inglés como Idioma Adicional (IIA)

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Abstract

This paper shows how an American International School in Vietnam has been using data and Learning Analytics to find out about students' learning from their assessments and how they use these findings to improve, among other areas, the reading skills of their mostly English as an Additional Language (EAL) student population. The source of data comes primarily from a Computer Adaptive Testing platform, commonly known as the MAP Growth test, which provides information about Math and Reading skills for each particular student.

The data provided is transformed and presented to educational stakeholders through visualizations created in specialized software in order to dig into the data and answer the pedagogical questions emerged from teachers and administrators. This process involves a new field known as Learning Analytics and Visual Data Mining in order to find new information not usually evident in school datasets. The results indicate that teachers get immersed in a reflective

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process that improves student learning through action plans informed by learning analytics (LA); which could be seen as the scientific data behind the observations educators have traditionally done.

Key Words: Data, Reading, Student Learning, Learning Analytics.

Resumen:

Este artículo muestra como un colegio internacional americano en Vietnam emplea datos y analítica del aprendizaje para conocer acerca del aprendizaje de sus estudiantes a partir de sus evaluaciones y los datos proporcionados por éstas para mejorar, entre otras áreas, las habilidades de lectura en una población predominantemente con estudiantes de Inglés como lengua adicional (EAL). La fuente es principalmente una plataforma de evaluación adaptativa por computador, comúnmente conocida como el MAP Growth Test, el cual proporciona información acerca de las habilidades en matemáticas y lectura para cada estudiante en particular.

Los datos proporcionados se transforman y presentan a los interesados a través de visualizaciones creadas en un software especializado a fin de indagar en los datos y dar respuesta a preguntas pedagógicas que emergen tanto de los profesores como de los administrativos. Este proceso involucra nuevos campos conocidos como Analítica del Aprendizaje y Minería Visual de Datos a fin de encontrar información que no es usualmente evidente en los conjuntos de datos disponibles en la institución escolar. Los resultados indican que lo profesores se ven inmersos en un procesos de reflexión para mejorar el aprendizaje de los estudiantes a través de planes de acción informados con analítica del aprendizaje (LA); la cual puede verse como los datos científicos detrás de las observaciones que los profesores han realizado tradicionalmente.

Palabras clave: Datos, Lectura, Aprendizaje estudiantil, Analítica de aprendizaje.

Resumo

Este artigo mostra como um colégio internacional americano no Vietnam emprega dados da analítica da aprendizagem para conhecer acerca da aprendizagem dos seus estudantes, a partir de suas avaliações e os dados proporcionados pelas mesmas para melhorar, entre outras áreas, as habilidades de leitura em uma população predominantemente com estudantes de inglês como língua adicional (EAL). A fonte é principalmente uma plataforma de avaliação adaptativa por computador, com frequência conhecida como o MAP Growth Test, o qual proporciona informação acerca das habilidades em matemáticas e leitura para cada estudante em particular. Os dados proporcionados são transformados e apresentados aos interessados através de visualizações criadas em um software especializado com o fim de indagar nos dados e dar resposta a perguntas pedagógicas que emergem tanto dos professores quanto dos administrativos. Este processo envolve novos campos conhecidos como Analítica da Aprendizagem e Mineração Visual de Dados com o fim de encontrar informação que não seja usualmente evidente nos conjuntos de dados disponíveis na instituição escolar. Os resultados indicam que os professores se veem submergidos em um processo de reflexão para melhorar a aprendizagem dos estudantes através de planos de ação informados com analítica da aprendizagem (LA); a qual pode ver-se como os dados científicos por trás das observações que os professores têm realizado tradicionalmente.

Palavras chave: Dados, Leitura, Aprendizagem estudantil, Analítica de aprendizagem.

Introduction

Assessment of student learning is a critical issue in education. There are different approaches, but so far personal professional experience seems to indicate that no matter how good the assessment is, it always falls short in determining what students actually learn, how they learn or what they are able to do with that knowledge. However, thanks to developments in technology, it looks like the assessment of learning is transcending the limits of linear and fixed datasets of questions on tests, to a stage where a computer software is able to determine the level of performance of students and adapt the test questions thanks to, among multiple tasks, the use of predictive algorithms and item response analysis. Even though in today's classroom Computer Adaptive Testing (CAT) is not a regular practice in daily assessment scenarios, they are gaining more space and preponderance in the internal structure of primary and secondary schools and eventually, as a result of the massification of technology, daily on-the-spot student adaptive assessment could take place on a regular and consistent way.

Current CAT platforms are usually equipped with basic dashboards and reports for different stakeholders, but sometimes the data analysis derived from these reports is limited by the possibilities of the platforms and a reduced interaction with the original datasets. If an institution is interested in digging into the data trying to find new patterns, associations between variables or merging data with additional datasets, likely it will not happen with currently available CAT platforms. As a result, organizations are being forced to find, implement and use new systems in order to enhance the internal analytics capability and to provide more customized and targeted reports that will illustrate, in a larger scale, associated variables to the test results.

This case study deals precisely with the above issue and its general objective is to illustrate how the analysis of data and insights from a computer-adaptive test can be enhanced by the use of a learning analytics system leading to the creation of action plans to improve student learning. It took place in an American International School in Ho Chi Minh, Vietnam, where most students are classified as EAL's and all subject teachers are considered EAL supporters.

The study uses the Measures of Academic Progress or MAP® Growth™ as the CAT platform and Tableau®[3] as the tool for learning analytics. As a technique to derive information and gain insights in datasets, this research used visualization analytics, sometimes called

Visual Data Mining, along with pedagogically-sound generative questions.

This paper is also an invitation for regular K-12 classroom teachers to explore the field of learning analytics and recognize that it is possible to improve student learning by digging into the data to derive information that can be used to inform, adjust and adapt the curriculum and instruction to the needs of the students.

Case presentation

Computer-adaptive testing platforms usually come with a robust set of analytics and metrics that provide comprehensive information to students, teachers, parents and school administrators. These analytics are used to make informed decisions about student learning, curriculum, learning plans, teaching or assessment among other educational variables. However, there are schools interested in digging deeper into the data to find additional information or relationships between other academic or organizational variables that often go beyond the pre-set reports provided by the CAT platforms, such as the identification of specific variables that affect learning or curricular areas for improvement. When this is the intention, CAT's analytics and reporting tools fall short, which means that other measures need to take place in order to better understand the whole student learning profile. This was precisely the case in an American International School in Ho Chi Minh, Vietnam, where it was found out that there are new questions that cannot be solely answered with the information provided by the CAT's toolkit, limiting the possibility of merging or integrating with other school datasets.

Even though the CAT platform known as MAP® Growth™ has improved the online reporting tools and produces more usable and comprehensive reports to inform students, teachers and parents; at the school level, there is a need for more information and insights that may surge or be constructed by combining additional school datasets.

The educational community is demanding more data insights and the currently available resources fall short. For instance, in the case of English reading, for one of the assessed areas it is not enough to know that the performance of the students is below the grade level expectation, or that the grade level RIT Average is 220. Teachers, administrators, parents and students would like to know in more details which areas they need to work on in order to improve their learning and performances, which eventually will be used to create action plans accordingly.

The research for this study indicates that a viable solution for an enhanced data integration and mining is the use of a methodological model aligned with the fundamental principles of learning analytics (Aristizabal, 2017). This model will allow teachers and school administrators gain deeper and finer insights as what to do with the data from the MAP® Growth™ and the implications that this new knowledge has on students' learning.

This case study took place in a school with 340 students and 32 faculty members over the course of a full academic year (2017-2018) with emphasis given to Math and Reading skills using the data provided by the MAP Growth Tests Suite and the school's information data system.

Conceptual references

In order to provide a theoretical framework to understand the reasons behind processes and techniques, this paper presents some of the most important concepts and connections between computer-adaptive testing, learning analytics and visual data mining as foundational principles and techniques to contextualize the methodology and conclusions for the case study.

Computer-adaptive testing

Even though the technology for more effective and efficient computer-adaptive testing is relatively new, the adaptive concept dates back to the very early days of psychological measurement. A brief description of the evolution of adaptive-testing is presented by Weiss (2004) who shows how from the Binet's IQ test, which comprised sets of test items normed by chronological age level to the current CAT, passed through research and development in the U.S. Military, in order to become what it is today: a "redesign of psychological and educational tests for effective and efficient administration by interactive computers (p. 72)".

When students take a computerized adaptive test, assessment takes place in a different dimension where what students are expected to know is not the fundamental principle, but rather what they are able to do with their knowledge. Each student enters their own reality where the difficulty of the questions is adapted and changed as a result of the student individual performance level. For Veldkamp & Matteucci (2013), the adaptability and computer-based nature of the test are factors that students tend to like more over a paper and pencil test, since they do not get bored by answering items that are too easy or too hard for them.

It is usually expected that final users of computer-adaptive tests trust the research and development behind the products and assume that the reports and information derived from these assessments correspond to an accurate picture of students' knowledge and skills. In the case of the MAP tests, the studies evaluate scores from the same students after a lapse of several months as opposed to several days, which produces reliability indices consistently above what is considered statistically significant (NWEA, 2016). Teachers and administrators usually use this information to make decisions involving actions to improve student learning like curriculum reviews, creation of individualized learning plans or many others striving for continuous school improvement.

Learning Analytics

Language and concepts evolve over time and learning analytics seems to be the evolution of something that humans have been doing for ages, which is making sense of surrounding data and information to construct usable knowledge. School teachers and administrators have always analyzed student data up to the level of the available technology and resources. In current times of the information age and knowledge society, the amount of data escapes the human processing capabilities and limited senses. The big data era is only growing bigger and bigger and it is spreading into every area of our lives. K-12 schools are already sinking in vast amounts of data which many times end-up in shelves or a couple of graphs in annual reports. However, such a wealth of information should be leading schools to ask themselves questions like:

- What kind of data do we have?
- How do we gather data?
- Do we collect all the data that we need?
- What are we doing with that data?
- Does the analysis of data have an impact on the greater picture? Does it improve teaching and learning?
- Can data help us be a better school?
- How do we know if what we do is actually working?

The reality is that today's schools are using more data than what they used to do some time ago, but likely it is still underutilized. Probably it is not the lack of resources, but mostly the lack of curiosity and interest to dig deeper into the different variables and connections of the pedagogical act.

An educational field where this curiosity seems to be blooming is the on-line learning environments and the computer mediated platforms (Papamitsiou & Economides, 2014, Romero, Ventura, Pechenizkiy & Baker, 2011), where experts in diverse areas like coding, statistics or psychometrics are using academic data to improve student learning and the conditions where learning happens. These experts generally use Educational Data Mining (EDM), which according to the International Educational Data Mining Society (2009) it is an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students, and the settings which they learn in. In general terms, as stated by Prabhu and Venatesan (2007), a data mining process, whether it is general or educational, involves any form of data analysis with the intention of finding patterns and regularities in sets of data.

It is interesting to notice that EDM is not a widely incorporated practice in face-to-face classrooms in K-12 schools, though it is in higher education settings and on-line or computer-mediated learning environments. This phenomenon is likely the result of factors like lack of awareness and technical knowledge across K-12 faculty, difficulties for data gathering and processing of big data in face-to-face classrooms, accessibility to user-friendly data mining software and poor practical and useful connections between mined knowledge and teaching practice (Aristizabal, 2017).

However, it seems like learning analytics (LA) offers a more familiar approach to educators, even though it can also incorporate educational data mining as one its tools to construct usable knowledge from raw academic data. As a developing field, LA incorporates the use of sophisticated analytic tools to improve learning and education by integrating fields like web, academic or action analytics, educational data mining and in general the application of the principles and tools of business intelligence to academia (Elias, 2011, Goldstein & Katz, 2005). Learning Analytics is a combination of processes where organizations, educators and learners gain insights in a timely manner to improve educational outcomes. It involves procedures like measurement, data collection, preparation, processing, reporting, interpretation of results and knowledge construction in learning ecosystems that facilitate decision making processes that affect learning itself, the pedagogical practice and the organizational dynamics (Knight & Shum, 2017, Papamitsiou & Economides, 2014, Aristizábal, 2017, Tempelaar et al., 2013).

Regardless of the learning ecosystem where it happens, learning analytics is the conduit to a reflective process aimed at improving curriculum, learning, teaching and assessment when multiple measures of academic data are effectively transformed into usable and actionable knowledge. As a mechanism for decision-making, educational stakeholders should be able to incorporate LA in short, mid and long-term strategic planning thanks to the possibility of analyzing learning progress from past, current and potential scenarios. Learning analytics, as a system, operates at several levels from students who learn about their own learning progress, passing through teachers who learn about their own students learning and their pedagogical decisions to policy makers and researchers (Shum & Crick, 2016).

Visualization analytics (VA)

Since this paper is also invitation for K-12 Educators to dive into the world of EDM and LA, the complexity and sophistication of coding and algorithms is phased out to give place to processes where epistemology and pedagogy, as drivers of professional practice, become the center of the knowledge discovery/construction in databases. In the end, teachers are the most interested parties in the monumental enterprise of improving teaching practice and student learning.

Educators, generally, do not have access to user friendly tools to carry out EDM in the classroom. A challenge is precisely to provide the mechanisms and specific tools and techniques for regular face-to-face education if the research field is meant to grow. As a challenge, EDM has to develop easy-to-use mining tools for educators or not solely for expert users in data mining (Romero & Ventura, 2007). Therefore, as a contribution to the popularization and democratization of EDM, LA and its methods, this research uses the concept of visualization analytics as technique to discover/construct knowledge from databases (Aristizabal, 2017). Not surprisingly, the 2011 conference on learning analytics and knowledge considered information visualization as a technique with the potential to offer interesting perspectives in learning analytics (Verbert et al., 2012).

As an integrated concept, visualization analytics aims at using humans' sight and intuition capacities to perceptually and cognitively gain insights over the exploration of visually exhibited data (Goebel & Gruenwald, 1999; Cook & Thomas, 2005; Chen, 2009; Parenteau et al., 2016) by integrating people and their combined abilities such as reasoning, critical thinking, pedagogical background, experience and personal epistemologies (Aristizabal, 2017, Keim, 2002, Romero et al., 2011), helped by the use of graphic and dynamic computer interfaces that maximize human capacity to perceive, understand and reason about complex and dynamic data and situations (Cook & Thomas, 2005).

Visualization analytics, visual analytics or visual data mining in a classroom involves a cognitive process where humans elaborate mental representations from graphically presented datasets. Thanks to the fact that "the human eye-brain system itself still remains the best pattern-recognition device known" (Goebel & Gruenwald, 1999, p. 22), it is possible for an educator to learn and understand the context, conditions, outcomes and, in general, the variables that affect teaching, learning, assessment or curriculum using visualization techniques.

Since the goals of EDM are to develop methods for exploring data that come from educational settings and to use those methods to better understand students and the settings where they learn; it is not speculative to say that visualization analytics itself is an EDM technique. Therefore, educators can use VA in order to learn about their practice, their students learning and how this learning happens by making use of their already built-in capacities, experience and situational knowledge. There is no need to be experts in databases, coding or programming, but someone must create these visualizations, interact with them and produce new ones based on individual or institutional needs. However, the knowledge discovery/construction is still within the educators' hands and key stakeholders.

Methodology

In order to carry out this case study, the following methodology was implemented:

Data gathering: The students in this study take the MAP Reading and Math Growth test during the fall and spring sessions. The test session for the whole school takes place during one week, including make ups. Once they finish, a CVS master file is downloaded with all the basic demographic and performance results. The school keeps and display the last 4 years of testing data.

Data processing: This process is key for a functional database and includes a series of sub-processes such as: a) cleaning, b) transformation and c) data integration. This stage of the methodology allows for the customization of the raw data and its integration with other available academic data such as IDs, year of enrollment, classes, teachers, periods, etc. The database integration is done in Tableau.

Data Analysis and visualizations. This stage involves the creation of a series of visualizations in order to enhance the reports from the computer-adaptive test. For example, the original platform provides visualizations about student performance by grade level, but does not provide this visualization over a period of time with filters to select different testing seasons. During this step the original datasets are enhanced as part of the LA system which allows gaining deeper insights through interactive visualizations that answer pedagogical questions.

Deriving actionable knowledge: Visualizations have no meaning without an intention provided by an epistemic individual, the process known as visualization analytics is used to perceptually and cognitively gain insights over the exploration of visually exhibited data. In order to facilitate this process, a series of guiding questions are generated to trigger inquiry and reflective behaviors. An enhanced visualization is one that uses the integration of variables not originally presented in the NWEA's reports, the use of analytical filters in dashboards and locally generated-data. These questions range from general ones such as... what is the current performance of students compared to previous years? To some more specific such as… what specific test goal my students struggle the most at?

Action plans: Since data is only useful as long as it has meaning and a positive impact on student learning; teachers by grade level teams are invited to participate in the creation of action plans in order to help students further develop the areas of high performance and reinforce those that require more attention. Since the MAP test results present student-centered data about their skills, students themselves are invited to create their own action plans to improve their performance, which is a strategy to help develop both teacher and student agency.

The enhanced reports and visualizations are presented to faculty right after each testing session, twice per year; and a report and an interactive dashboard are shared with all staff for easy access on demand. Dashboards allow teachers and administrators see and interact with updated-graphically-presented-information that facilitates access and interpretation of data for the decision-making process (Aristizabal, 2016). After each sharing session, there are two follow up meetings within a 4 month period to determine the actual use of the visualization, updates on action plans and possibly new visualizations based on particular needs or the emergence of new pedagogical questions.

Results and enhanced data analysis

As mentioned before, an enhanced visualization uses the integration of variables not presented in the original reports, integrate locally generated-data and use analytical filters in dashboards for easy access and interpretation. However, a visualization is an inert graph without an educator behind it to make sense, assign attributes, derive information and gain insights to better understand how teaching and learning happen.

The following examples correspond only to a sample of enhancements through visualization analytics that are not originally available in the test platform. The goal behind is to help understand the learning process through a series of results, immerse in reflective pedagogical thinking and engage in a continuous improvement process. They were generated using the pedagogical questions proposed both by faculty and school administration.

Are our students experiencing reading learning growth in each testing session?

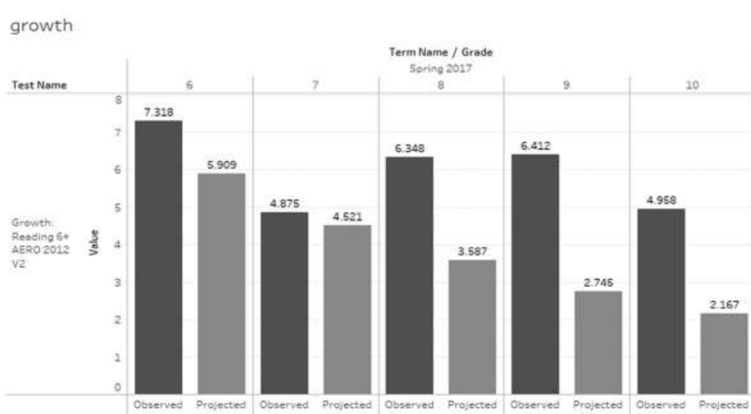

Figure 1. Average Projected vs Observed Growth by Grade Levels.

This visualization shows that for this testing window, in average, the students performed above the projected growth. However, thanks to the dynamic filters, it is possible to identify specific students who are not exhibiting growth (Figure 2), which is used to plan some interventions and represents a level deeper into the data.

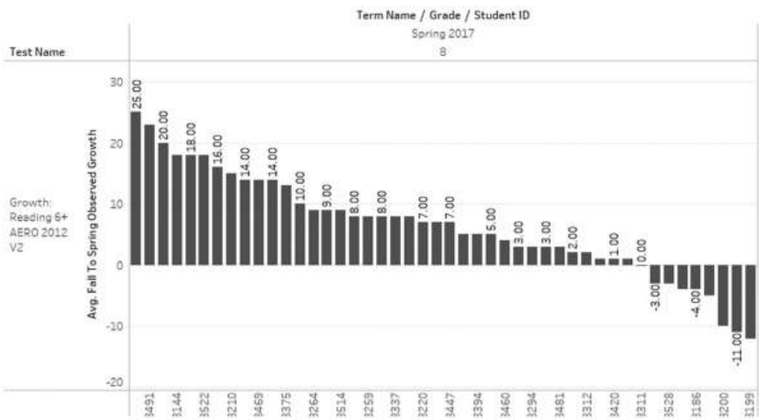

Figure 2. Observed growth by grade level

b) Who does need specific interventions and follow-up?

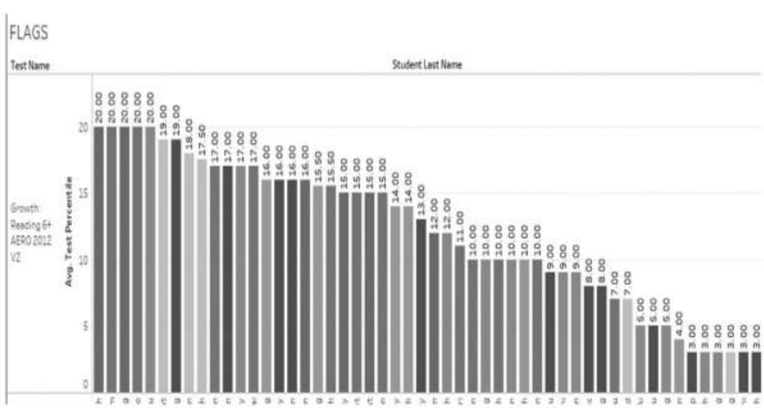

Figure 3. Students below 20th percentile

Even though this information is readily available in test platform, versatility and ease of access with dynamics filters in dashboards, make it possible to identify students below or within a certain percentile range for a particular test, session and grade level. With this information teachers and counselors have individual conversations and plan personalized learning strategies for students. Since the performance of students can be affected by external factors, prior to any intervention, there are conversations with students to determine some possible causes and plan for a re-test, if needed, for more valid information. This particular strategy allows an early identification of students for individual interventions and follow-up, so no students fall through the cracks. Each bar corresponds to a particular student and each color is a specific grade level.

c) Is there any particular area we should review in our curriculum?

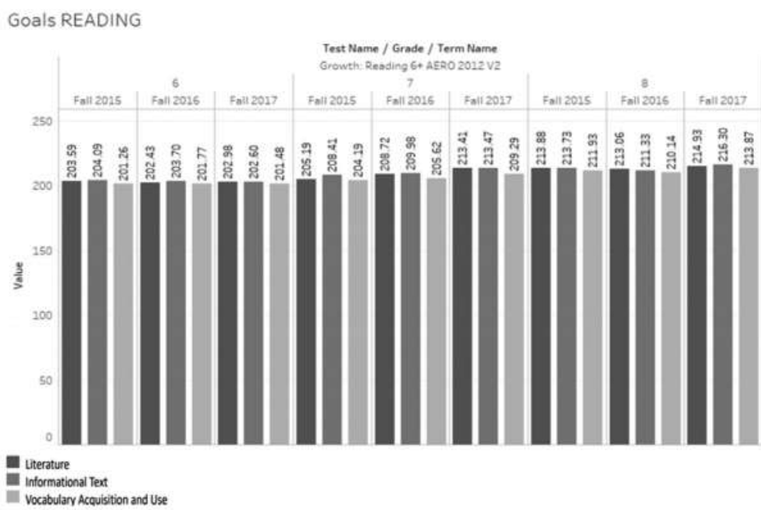

Figure 4. Average score (RIT) by Goal.

This visualization shows that the goal labeled as "Vocabulary Acquisition and Use" has historically been the lowest over the last 3 years in every grade level; information that has been used by all teachers, not just EAL or English language Arts, to engage in conversations about strategies and adaptations in order to fill-in the curricular gaps and help students develop their corresponding competencies.

d) Does time on test have any impact on student performance?

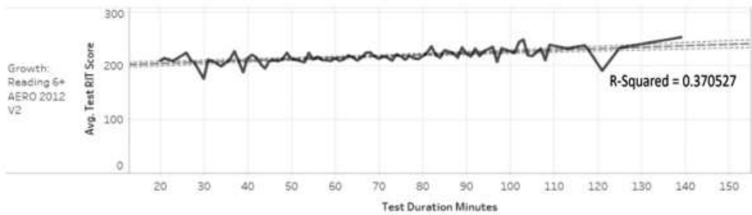

Figure 5. Time on Test versus Average Score (RIT).

The original test platform provides data time for students in each test, however, it does not show the relationship between the score (RIT) and the time spent. This enhanced visualization provides a linear trend model including a p-value to understand the significance of the model. For this particular test, it was clear that students that spend more time engaged on the test, tend to have higher scores. With this information teachers are more attentive to the time and engagement of students during the test to motivate them to try their best. The original test platform now includes a new option related to student engagement which teachers use to monitor students in real time.

e) Given that we are an international school with a high percentage of EAL students, is there any relationship between the year of enrollment and the student performance on the test?

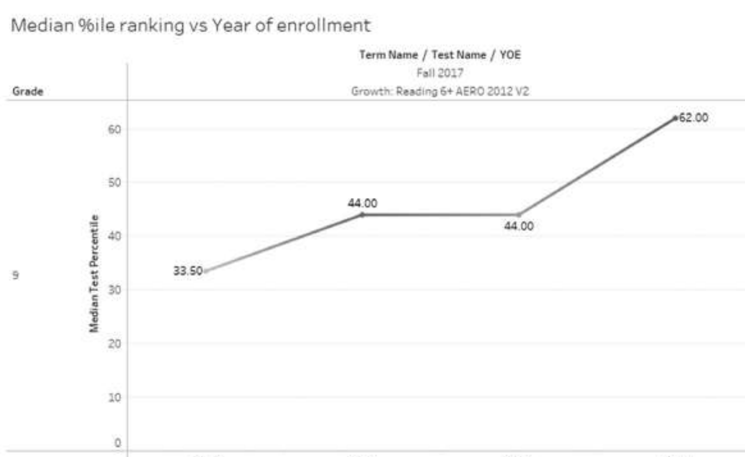

Figure 6. Median Percentile Ranking versus Year of Enrollment.

Thanks to the integration of data, it is possible to link students with their corresponding year of enrollment. In this case, this visualization indicates that it is more likely for a student in the same grade level to exhibit higher performances the longer they have been enrolled in school, which is probably due to factors like familiarity with the test, confidence and academic experiences. This visualization has been used by the school administration to show the added-value of being enrolled in a school with a strong EAL support.

Discussion

Learning Analytics (LA) is a combined technical and cognitive process where academic stakeholders engage in analytical reasoning to gain insights about teaching and learning in order to improve students' learning and how it happens. It involves the gathering, processing and visualization of data and, of course, the intervention of an individual(s) to ask questions, derive information and construct meaningful knowledge to better understand and improve the pedagogical act.

Enhancing data analysis with LA implies going beyond standard reporting to a stadium where there is integration with other sources of academic data, the development of pedagogical questions and the possibility of transforming data into information and constructed actionable knowledge, in this case, through visualization analytics facilitated by a convenient technological platform.

From the technical perspective, LA requires some data management skills to collect, store, process and report data in ways easily understood by stakeholders, mostly teachers, and the flexibility and ease of use of a software to interact and transform data into insightful information. The component that links the technical and cognitive aspects in LA is visualization analytics, understood as a methodology to learn about the learning process thanks to the possibility of answering pedagogical questions through an exploratory process of educational variables. A visualization gains meaning when an epistemic subject derives information from it through an analytical and reflective process that makes use of their professional knowledge, skills and competencies. This way the individuals connect what they already know and are able to do with the new information which in turn develops new understandings and alternative operating scenarios.

Visualizations in Learning Analytics tend to be dynamic, allowing the user to interact with the interface to make modifications or adaptations to explore datasets, play with different variables and find alternative associations between educational variables. This possibility, enabled by technology, is perhaps one of the most important characteristics of LA since it allows the user to interact with the visualization, dig into the data, visualize multiple variables at the same time, apply filters and many times find patterns never thought of before. When the discovery of new information takes place, the exploration of data with visual analytics falls into a category known as Educational Data Mining, where visual data mining is considered a technique.

In this case study, faculty and school administrators where able to answer particular pedagogical questions, generated new ones and developed action plans to improve students' learning. The enhanced reports, facilitated by a technological platform and a Learning Analytics Process, derives in meaningful insights that help inform teachers' actions and school's strategic learning plans. Teachers become more aware of the general and individual learning needs and administrators engage in actions to support teachers in their particular classroom endeavors.

Learning Analytics allows teachers to learn about the students from the big picture to individual or particular cases. In this study, as a school-wide finding, teachers became aware that reading is an area that requires support from all subjects and that the development of vocabulary is a shared mission. Action plans were created by grade level teams, showing that every single subject area is responsible for the development of activities, learning scenarios and opportunities that allow the students develop the skills needed to improve their reading skills. This is a shared responsibility where all subject teachers are EAL teachers too.

Some particular shared reading/language development strategies emerged from the grade level action plans include:

- **Word of the week:** Every week there is a new and interesting English word that is displayed on posters around the schools with examples about its use and possible meanings depending on the context. The space between steps in stairs is also used to display words of the week in such a way that students going up the stairs can constantly read the word and see their meaning. Teachers are also encouraged to include these words in their regular classes.
- **EAL-Subject teacher collaboration**: EAL teachers engage in conversations with subject area teachers about particular readings for students depending on their reading level and assign same topic readings with different levels of difficulty using Newsela as a learning tool. This collaboration, in some cases, involves the

EAL teacher carrying-out a series of activities in regular classes to help students develop their English proficiency. For example, note taking and reading strategies, games for vocabulary acquisition, websites with exercises for pronunciation, etc.

- **EAL extra-support for students with low percentile ranking.** As part of the Grade-Level Action Plan, students identified below the 20th percentile ranking (See Figure 3) receive extra-EAL support targeted to their particular needs. Individual Educational Plans are being created to follow-up on these students. For these cases, more pieces of information are usually used like their WIDA Test Score, classroom grades and teacher comments.
- **Co-teaching**. EAL teachers work with subject teachers in the classroom to provide students with language development strategies through subject areas and specific language learning.
- **Co-planning.** EAL teachers support subject teachers in the development of units of study linking the development of language skills and the subject content.
- **Parallel Assessments**: Students can be assessed independently both by the subject teacher and the EAL teachers from their respective fields. Feedback is provided from both perspectives.

Conclusions

This case study was an opportunity to reflect on some institutional practices about the use of data to improve student learning, particularly reading skills after gaining insights through a new field called Learning Analytics. This study leads to the following conclusions:

Learning Analytics has been in schools since the time they started collecting and using data to make decisions; the difference now is the possibility of integrating different databases, transforming data and reporting in interactive ways that facilitate the decision-making process, reflection and knowledge construction processes. Learning Analytics is only meaningful and impactful when teachers use their pedagogical and epistemological backgrounds to reflect on their professional practice and make decisions as to what is best for students' learning.

Data is only meaningful when it is used to respond to pedagogical questions emerging from teachers' experience and professional observations. It is a way to learn about the student as an individual who has particular strengths and areas for improvement.

Visualization analytics is an exploration method that helps answering pedagogical questions and fuels professional discussions around students' learning.

A Learning Analytics system in a school is a mechanism to efficiently use data for informed decision-making, which involves decisions at the classroom level, like particular differentiation strategies for students; or at the grade level, like shared or common strategies, for example for vocabulary development; or at school level, like benchmarking or curriculum monitoring.

In a Learning Analytics process the use of a user-friendly platform is essential since many teachers usually get discouraged by the use complex and hard-to-understand software. A facilitator is highly recommended in order to prepare and interact with the visualizations and so allow more time and space for teachers to be engaged in the information derivation and the knowledge construction processes.

The continuous monitoring through interactive dashboards and LA indicates that there has been a steady improvement on students' language skills after the implementation of action plans and the combined teaching strategies.

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