EXPLORING THE POSSIBILITIES OF APPLYING BUSINESS INTELLIGENCE TO LEARNING MANAGEMENT SYSTEMS DATA TO ENHANCE STUDENT LEARNING

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ABSTRACT

Learning management systems create a large volume of transactional data that can be used by both the instructor and the student to enhance the student's learning of the course content if an effective way can be found to use the large amount of data. This paper describes an architecture that uses learning analytics, educational data mining, and business intelligence processes to analyze the data to identify patterns in student behavior that lead to the probability of certain outcomes. The results of these analyses provide facts that instructors and students can use to provide proactive information and feedback to potentially help students improve their knowledge, skills, and performance in a course.

INTRODUCTION

Learning technologies are common in the education industry as parents, students, and teachers try to take advantage of the technologies to promote and improve learning. Common in many educational institutions are learning management systems (LMSs), a specific type of learning technology that is often used to automate the administration, documentation, tracking, reporting, and delivery of e-learning education courses or training programs. LMSs have been instrumental in the expansion of online learning environments [4]. For example, Chico State University has rolled out experimental course redesigns, encouraging faculty members to think about how to use new learning technologies such as online instruction [7]. Carnegie Mellon's Open Learning Initiative and the Monterey Institute for Technology and Education's National Repository of Online Courses are other examples of innovative uses of technology to help educate students [10].

There are benefits to the use of LMSs. The use of LMSs to manage course content allows for the capture of student behaviors such as when students access reading materials and teaching notes, when students start online assignments, how long students take to complete assignments (including quizzes and exams), and the timing and volume of student contributions in discussion forums. While many LMS capture this kind of information, little is known about how to appropriately use the information to better understand student behaviors and to enhance student learning. Furthermore, the large volume of available data makes interpretation by conventional means problematic. Thus, instructors who use LMSs in their teaching may not use the available information to inform their teaching.

This paper presents an architecture that utilizes the transactional data from LMSs to provide reactive and proactive communications to students to facilitate student-instructor interaction in the online learning environment. The architecture that we describe can be used both to provide automated feedback to students and to provide instructors with information that they can use to manually initiate instructor feedback to students. Effective automated student-instructor interactions can potentially lead to successful scalability of online courses, where success is defined as higher student retention, completion, content retention, and skills development. We begin by reviewing the literature relevant to modes of interaction, learning management systems, and the use of agents in the virtual learning environment (VLE). Then we present our architectural design with two examples of its implementation. We conclude by presenting and discussing the results of the architecture design, making recommendations for future research and practice.

REVIEW OF RELEVANT LITERATURE

The learning management system literature suggests that the data in LMSs can be used to improve the online learning experience for students by facilitating interactions that are important to student learning. Anderson identifies six modes of interaction in learning: teacher-content, student-content, student-teacher, teacher-teacher, content-content, and student-student [1]. He points out that while interactions are important in learning, different students may have different preferences for interactions; for example, some students may pick learning opportunities that minimize certain interactions, such as student-student (e.g., they might prefer to avoid classes with teamwork) or student-teacher (e.g., they might prefer large classes) [1].

Anderson argues that student-teacher interaction "…has the highest perceived value amongst students, and thus commands highest market value" [1, p. 4], but it "…is generally the least scalable type of interaction, and thus is usually substituted for by student-content interaction in mass education systems" [1, p. 5]. He argues that "Some student-teacher interactions can be automated … through the development and use of content resources, and especially those utilizing autonomous teacher agents" [1, p. 4]. These agents can be developed with the use of learning analytics.

Ferguson traces the development of learning analytics in technology-enhanced learning [6]. She examines how the growing use of learning management systems (LMSs) and other virtual learning environments (VLEs) have resulted in the availability of large amounts of data (big data), which results in a technical challenge: "How can we extract value from these big sets of learning-related data?" [6, p. 306]. She points out that getting value from big data is especially relevant with the growth in online learning: "How can we optimize opportunities for online learning?" [6, p. 207]. She also recognizes the importance of getting value from big data because of a growing expectation from the public and from policy makers that educational institutions will measure and improve performance: "How can we optimize learning and educational results at national or international levels?" [6, p. 207].

[12] examine the similarities and differences between two distinct but related strands of research: educational data mining (EDM) and learning analytics and knowledge (LAK). They adopt the definition of EDM from the International Educational Data Mining Society: EDM is "…concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in" [12, p. 252]. And they adopt the definition of LAK from the Society for Learning Analytics Research: LAK is "…the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [12, p. 252–253]. In comparing EDM and LAK, [12] argue that LAK focuses on data analysis that enhances the human judgment of students and teachers about learning while EDM focuses on automating data analysis through computer systems such as intelligent tutoring.

[14] examine different definitions of analytics to develop a conceptual framework that incorporates the following components: business analytics, academic analytics, learning analytics, predictive analytics, actionable intelligence (action analytics), and decision making. They argue that "…learning analytics focuses on two areas — learning effectiveness and operational excellence — with the latter referring to the metrics that provide evidence of how the training/learning organization is aligning with and meeting the goals of the broader organization. Learning analytics … is focused on the learner, gathering data from course management and student information systems in order to manage student success, including early warning processes where a need for interventions may be warranted" [14, p. 6].

[11], [15], [16], and [8] discuss the value of providing learning opportunities within the virtual learning environment to achieve better learning. They all contend that by providing students with meaningful interaction that allows the students to be active agents in the learning process, students do perform better. The researchers stress that taking opportunities as provided by technology-enhanced tools can be a mindful process wherein students are active agents in the learning process as long as the tool has a learning benefit [5] [11]. Their results contend students should be knowledgeable with respect to: (a) the learning context and the learning needs that arise from it, (b) the tool functionalities, and (c) the relationship between the tool(s) and the learning needs. In other words, not only do learners need to recognize the learning opportunities as provided through the learning tools, learners have to be able to use these tools adequately. Hence, as a second learner condition, learners have to be able to use the selected tools skillfully [15][16]. In addition, a learner has to be considerably motivated to spent effort and time in taking the learning opportunities since it requires considerable effort for unclear gains [11] [15][16]. We suggest that facilitating the student-teacher interaction can help students better identify the tools that work best overall to help them identify the tools that can help them learn.

Thus, we build in this paper on the ideas from the prior literature for developing student-teacher interactions using learning analytics and business intelligence to generate agents that direct students to tools available in the learning management system. Our architecture can be used both to enhance student learning and to demonstrate the achievement of educational excellence to stakeholders such as accrediting agencies and policy makers. The proposed architecture can be used by teachers and educational programs to enhance learning by better utilizing the big data that can be available in LMSs and other VLEs. We illustrate our architecture with two examples: one from an LMS, and the other from a Web-based business simulation game (which is an example of a VLE different from an LMS).

The architecture that we propose in this paper can integrate the EDM approach and the LAK approach. We provide one example of our proposed architecture that is incorporated into a learning management system (LMS) to inform teachers about students' progress through the learning content in the LMS so that teachers can make better judgments about student learning, thereby improving student-teacher interactions, which illustrates the LAK approach. We also provide one example of our proposed architecture that is incorporated into a Web-based business simulation game that both informs teachers about students' progress through the game and utilizes intelligent agents built into the game to provide automated feedback and advice to students, thereby both improving student-teacher interactions, which illustrates the LAK approach, and reducing teacher workload while improving student-content interactions, which illustrates the EDM approach.

METHODOLOGY

The use of learning management systems (LMSs) has strengths and weaknesses. A major strength of LMSs is the availability of learning activities and tools 24x7. Furthermore, the centralization of assignment details, discussion forums, and learning material provides the instructor with a rich dataset of transactions that capture student behaviors, including information about when the student logs in to the LMS, what the student did while logged in, and the results of the student's learning activities. Some LMSs can tell the instructor the proximity of IP addresses of students and the addresses of other websites the student visited while logged in to the LMS. A weakness of LMSs is that the LMS-generated data is not easily available in a manner that can help the instructor better understand and identify behaviors of the student while online and help the instructor help provide feedback and guidance to help the student improve their performance in the class, much like the instructor would do in a face-to-face situation.

We describe an architecture that aggregates the information and then uses reports and intelligent agents to guide students; the architecture can provide proactive as well as reactive assistance to help the students understand how their behaviors could impact their overall performance in the class as well as the results of their behaviors. We begin by describing the data typically available in the LMS, then introduce Empowerment Analytics; we demonstrate how the implementation of Empowerment Analytics is being used to provide guidance and feedback to the student, thereby simulating the student-teacher learning mode.

The physical design of the system works with most commercially available browsers; no plug-ins or other third party software is needed on the student's computers; no modification to any security related browser setting is required.

Data Available in Popular LMSs

There is much data available in the LMS about the use of the LMS. All of the data is available for each user, and includes information such as the login history and when and how long the user accessed each element of course content in the LMS. The system also holds data regarding the number of times a student takes a quiz, how long it took for him or her to save an answer, and how long it took the student to complete the assignment. The problem is that there is no easy provision for analyzing all of the student data to find patterns unless the instructor is willing to download LMS data details and then examine and interpret the large volume of data. Thus, the reports and the reporting are both limited and limiting. Instructors can at best do a cursory analysis of where the problems are in the course and with the students. The data, though, is there, and it could allow the instructor to perform a more in-depth analysis that potentially enriches the online experience for the student if there were tools available to more easily access the data and generate reports that are helpful to both the student and the instructor. Sample user data items are shown in Table 1.

Table 1: User LMS Data Items

Item Name	Description
UserID	The unique identifier of the student
Last login	The last day and time the student logged in to the LMS
DateA	One for each day of the class
DateA-Number of Sessions	Number of times a student logged in on Date A

Also available is event monitoring data. Typical data items from event monitoring are listed in Table 2.

Table 2: Event Monitoring Data

Item	Description
UserId	Student identification
Keyboard activity	The keystrokes are associated with an element within a given piece of learning content.
Mouse activity	Clicks associated with an element in the learning environment.
Viewlength	What portion of the learning content is viewable on the user's screen at a given time.
ViewTime	How long the user viewed the site.
ViewActivity	Did the viewer scroll through the page or immediately go to the bottom (generally this happens when there is a link for a quiz at the bottom of the page.)
OtherLinks	What hyperlinks were pressed on the page?
EmbedUse	Were embedded help facilities requested/viewed? Time spent on those facilities.
LearnerPath	What was the learner's path the learning objects? Depth first vs. breath first vs. random walk? Where there many circuits in their path?

Introducing Empowerment Analytics

Empowerment Analytics (EA) is a concept that combines learner analytics with business intelligence to empower students to improve their learning, studying, and engagement behavior to improve performance and retention from a course. The architecture incorporates current user data with aggregated data from prior courses to provide current students with information regarding how certain behaviors impact overall course performance as well as performance on specific assignments or exercises.

Specifically, it uses business intelligence processes to profile the characteristics of historical performance. Business Intelligence (BI) is defined as "a system for analyzing collected data, with the purpose of providing a better view of an organization's operations to ultimately improve and enhance decision-making, agility and performance" [13].

BI processes are used to answer questions such as:

- How did students perform overall?
- What happens when a student misses the first week of the course? Second week? Stops working in the fifth week?
- How many students stopped participating in discussions after the first week?
- How many students stop participating in groups? Did the group participation differ based on the week the assignment was due? Did the participation differ based on enrollment type (e.g., student major)?

The architecture then uses the learner analytics processes, particularly statistical analysis, data mining, and predictive modeling, to address questions such as:

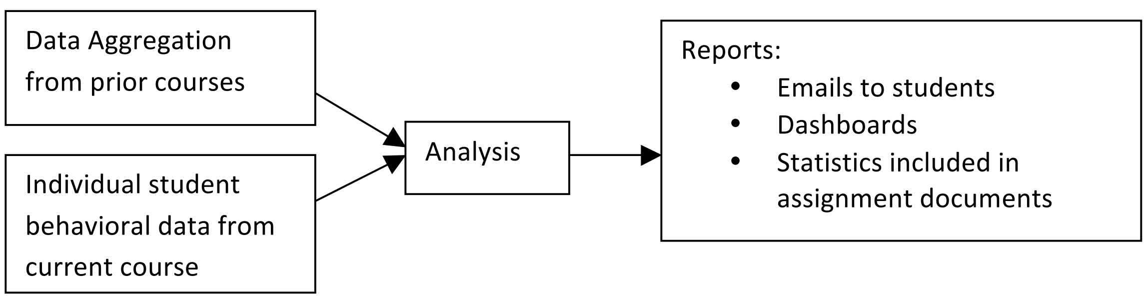
- What is the probability of a student not participating in groups to pass the Team Knowledge, Skills, and Abilities (KSA) assessment?

- What is the probability of a sophomore student passing the writing assignment at level 4 of the writing rubric?
- What is the probability of a student who starts the class after the first week earning an A, B, or C?
- What is the probability of a student who doesn't watch the video associated with an assignment earning a particular letter grade on that assignment?
- What is the path (different tools used and the path used) by students to earn the best scores on certain types of assignments?

We use the business intelligence processes to report using either written communication or a dashboard to provide student with the relevant information to guide their behavior in the course and on specific assignments.

The design of the architecture is illustrated in Figure 1.

Figure 1: Empowerment Analytics Model



The data is aggregated at the first step and then analyzed to provide proactive as well as reactive communication to the student. Proactive communications are statements like "Students who earned an A on this assignment started an average of two weeks before the due date" or "Students who passed this assignment watched the video lecture at least one day before beginning the assignment." Reactive communications would be statements like "Students who earned a D on this assignment tended to not pass the Chapter 12 and Chapter 13 assignments. Please redo the assignment to improve your chances of passing the course." Similar displays are shown on the dashboards and included in assignment documentation. Each component is described further in the following sections.

Data Collection and Aggregation

The heart of the architecture is the aggregation of both historical and current detailed activity data. The historical data is needed to develop path analyses and statistical information of how previous learners performed with certain behaviors. The current data is used to develop the appropriate question and response that the instructor would generate in a face-to-face environment. The collection of the detailed activity data does in no way represent a compromise of the LMSs' or browser's security protocols; all of the information can be obtained from the LMS database with the exception of the event-based tracking.

At the core of the raw data generation subsystem is the event-based programming environment supported by virtually all modern Web browsers. This subsystem allows Web-based applications to detect and react to users as they interact with the system. For example, when a user types something into an input box on a Web form, each keystroke is signaled to the browser as an event. Many applications will capture this event for helpful purposes such as automated input completion, error checking, or interactive form generation. There are many events recorded by most browsers. A somewhat nontechnical explanation of event programming is available [3].

The raw data generation scheme is a general framework. Some student-teacher interactions can be developed without event programming while some rely completely on the event programming. We show designs that use only LMS data and another that uses the LMS data, the VLE data, and the event programming data.

Analysis

An advantage of teaching in a small classroom environment is that the instructor has the opportunity to gain first hand understanding of each student in the class. The instructor will get a sense of the student's perceived intelligence, ability to work in teams vs. independently, commitment to the course, level of understanding of the material covered, and so forth. Then, based of these perceptions, instructors frequently subconsciously adjust the volume and detail of advice given to the students. In essence the instructor builds an informal user rating metric for their students; the instructor's interaction with the students is in part determined by this metric. Over the duration of the course, this informal user metric is likely adjusted as the instructor has further interaction with the student.

Building in the instructor's mind such an informal metric about each student is feasible in a small classroom environment where the instructor may have direct, firsthand interaction with the students. Unfortunately, this does not scale to a large classroom environment or to online learning where instructors may have little or no firsthand knowledge of their students. Customizing the delivery of the course material to meet the needs of an individual learner can be a difficult proposition in large classes or in online classes.

The architecture for Empowerment Analytics attempts to parallel the construction of this user rating through electronic means, and makes the interaction scalable to larger classes. Using the raw student activity data and an instructor-driven benchmark, a user rating score is derived. This score is computed as an affine calculation based on a student's performance on a series of scorecard items. These items are the data elements described in sections 3.1 and 3.2, which are items that are measurable; they represent performance activities that may be observed in the activity logs. These scorecard items should be easily extensible though the details will vary from environment to environment.

Ascribing meaning to the raw data generated in the previous section is difficult without a benchmark to measure the activity against. For example, suppose the activity data indicates that during a portion of the course that student online activity dramatically fell. From an educational perspective, what is the meaning of this finding? It is very difficult to tell. The lack of online activity may have been caused by many reasons: the course is engaged in non-online content or activities or the students are on a break. Student activity only has meaning when coupled with the expectations of the instructor. For example, the decrease in activity is an area of concern only if the course is at a point where the instructor would expect the students to be heavily engaged with the online content. Thus, to provide meaning, the data need to be interpreted in light of the instructor's activity benchmark expectations of student behavior and performance.

Building these activity benchmarks becomes a metric of performance through which success in the LMS may be measured, with the activity benchmarks providing meaning to the student's activity. These benchmarks allow the instructor to communicate with the LMS the expectations the instructor has for the student. This is a key component because it allows measurements concerning the alignment of student activity and instructor expectations. For example, when an instructor is working on an activity within the course, one would expect that the students' traffic patterns on the supporting materials for that activity to dramatically increase. If this increase fails to occur, this would be a misalignment of the student activity with the instructor's expectations, and would thus be an area of concern. This alignment can be measured, which provides a means of progress-tracking the student activity.

These benchmarks are particularly helpful to instructors who regularly teach the same course. These benchmarks are maintained across terms and may be statistically correlated with other performance measures within the course. For activities that are repeated across terms, the students' activity patterns may be correlated with their final activity score recorded in the gradebook, and may be correlated with their final letter grade in the course. For large class sizes, statistical significance of these correlations tend to happen quickly. Also, the combination of the benchmark performance coupled with the student activity provides a knowledgebase for a wide variety of data mining tools.

It should be noted that this benchmark-activity alignment does not guarantee any performance outcome for a specific student or for a specific course. The intention of this alignment is not to attempt to predict the future; it cannot tell an instructor what final grade a student will receive on an assignment or in the course, but it can provide students with statistical statements, indicating the propensity of a student or class to perform in a certain manner based on historical performance data. For example, the alignment architecture allows statistical statements such as "75% of the students who started the assignment the night before it was due did not complete the assignment on time. Those that did complete the assignment on time spent an average of 15 hours completing the assignment." Students receiving this statement at the maximum time given for the start of the assignment are then "empowered" with historical facts to guide his or her behavior; students are no longer able to use excuses such as "I didn't realize it would take me 15 hours to complete this assignment."

The benchmarks can and should be refined over time as the course curriculum evolves or as the instructors expectations improve. Misalignments between the benchmark and the student activity can drive a continuous improvement process for the curriculum. If disappointing alignment results are seen repeatedly across terms, this may be an indicator of a potential area for curriculum improvement.

Reporting

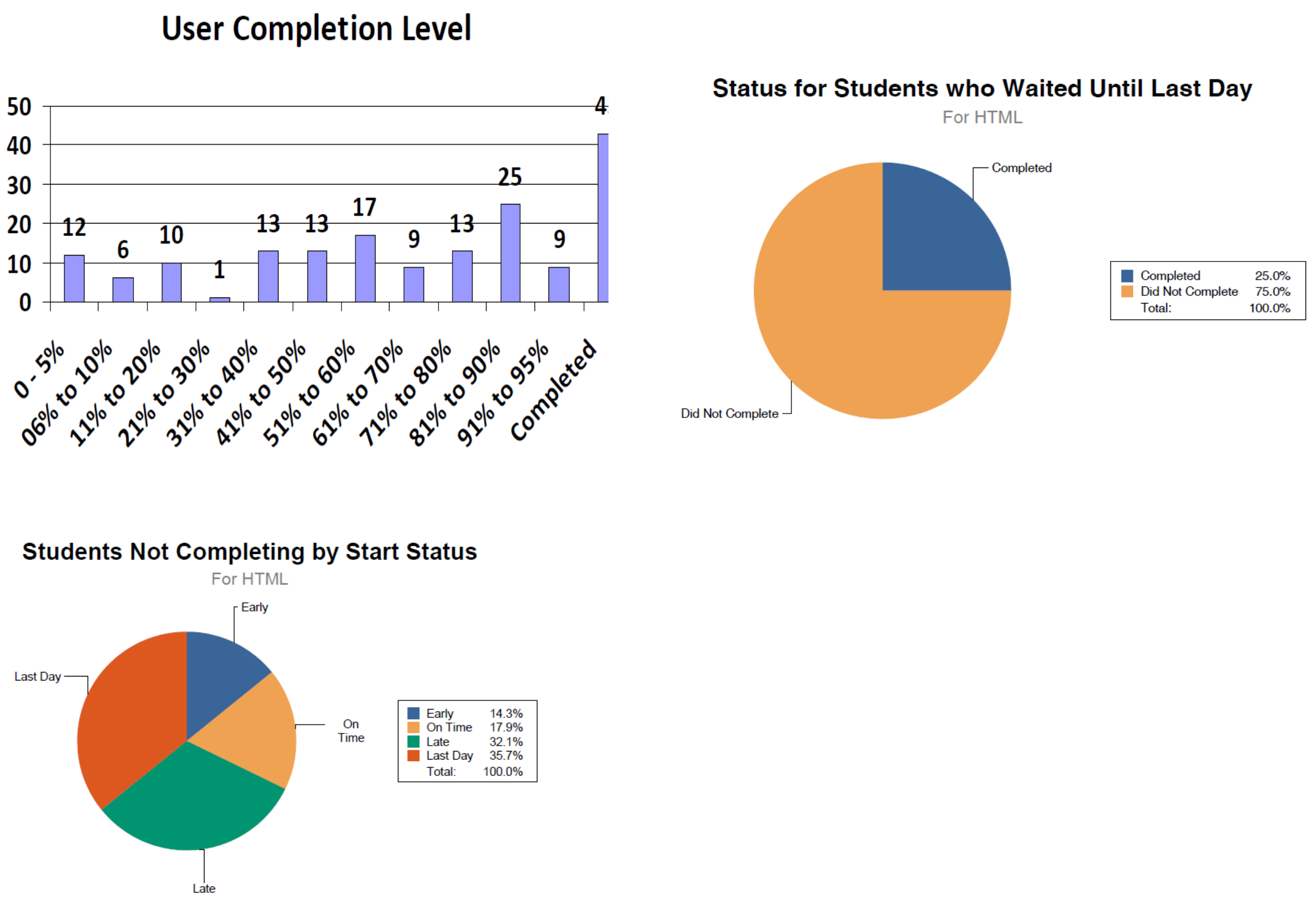
We provide two examples of the implementation of our architecture. The first example is from the Aspen Learning Management System (in the next section), and the second example is from Micromatic, a Web-based business simulation game (in the following section). The two examples illustrate different ways that our architecture can be implemented depending on the instructor and the purpose of the learning tool.

Example: Aspen LMS

We provide as an example the implementation of the Empowerment Analytics approach to the Aspen LMS [2]. Aspen is being used in a large (250 student) Introduction to Management Information Systems (MIS) course at a mid-sized public university. The course is a project-based course only; there are no objective exams in the course. Students work either individually or in teams on a series of large, complex, multi-week MIS-related projects. The vast majority of the content for the course is delivered through the Aspen LMS. The student activity monitoring has been in place for the most recent four semesters.

At the beginning of each semester, the instructor informs the students that the activity monitoring is in place. Students are told what type of activity is tracked and are shown sample reports from previous semesters. At weekly intervals during the student's work on the various projects, the instructor will show in class course-level activity reports for the current project. The charts in Figure 2 are examples of the charts shown.

Figure 2: Aspen Student Activity Reports

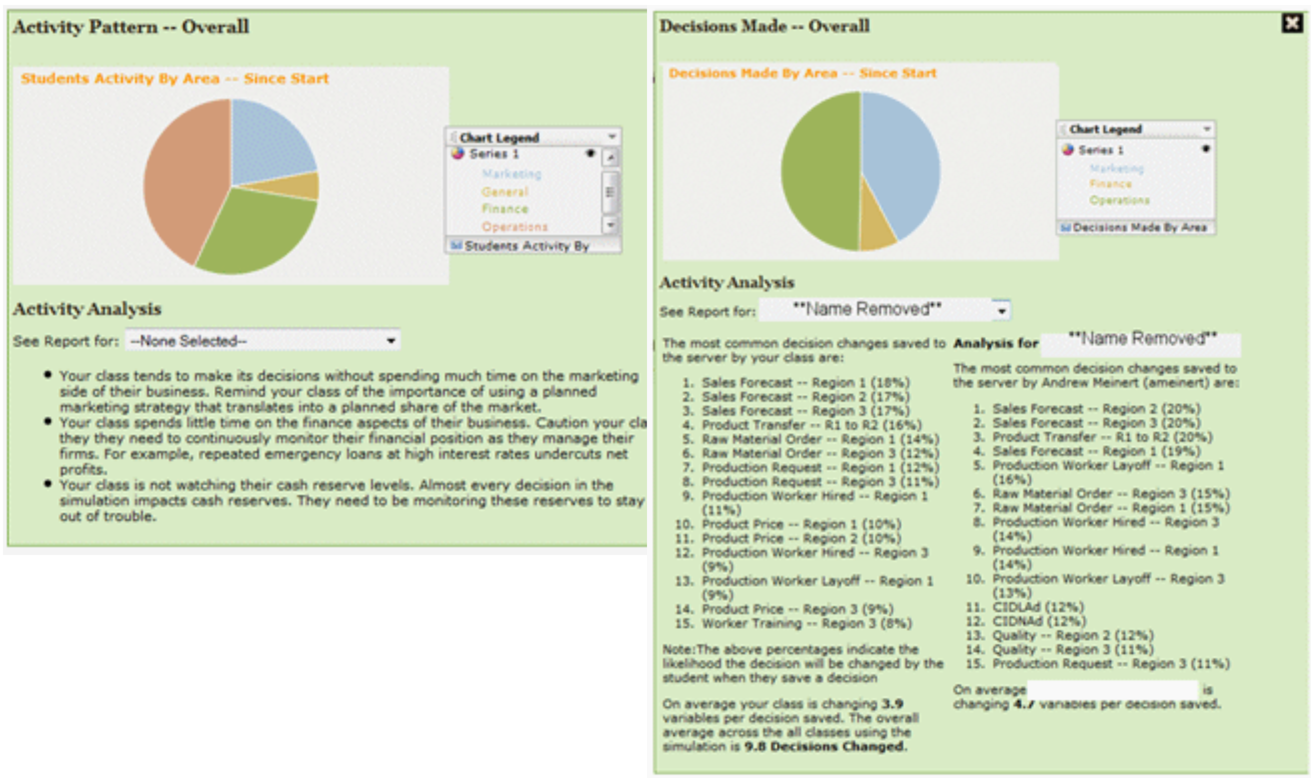


The instructor's perception is that overall the student monitoring has a positive effect on the course. It is frequently noted that student activity increases immediately after the presentation of the charts. The monitoring is also used as a feedback mechanism for the course. Based on how the students interact with the material order and amount of time spent on various pieces of the course, content continues to be adjusted by the instructor. The monitoring also assists the instructor with individual student interactions. The monitoring is used when advising individual students who may be have difficulties in a project or in the course; by understanding the student's work protocols through the course content, the instructor can more effectively advise the student on ways to improve their performance. Also, the monitoring is useful when resolving disputes between the team members of the student-project teams. Inter-term performance on the class activities continues to improve. More students appear to heed the instructor's warning to start the assignments early and to work consistently on them over time. These findings are heuristic only; other factors may be influencing these performance changes.

Example: Micromatic Business Simulation

Parts of Empowerment Analytics have been implemented in Micromatic [9]. Micromatic is a commercially available business simulation that is used by many colleges of business. The typical courses that employ the simulation are Principles of Management, Entrepreneurship, and Business Policy and Strategy. Micromatic offers a wide series of activity monitoring to the instructors. Figure 3 shows several examples of these reports.

Figure 3: Micromatic Student Activity Reports



These reports are intended to provide the instructors insights about student participation in the simulation. The reports go well beyond monitoring the amount of time/effort the students are spending. The reports help the instructor to understand which parts of the simulation the students are focusing on, and where their strengths and weaknesses lie. Each report contains a course level section while also allowing the instructor to drill down to an individual student (see, for example, the “Decision Made -- Overall” report in Figure 3).

One of the most significant goals of this architecture is to adapt the learning environment based on the learning system’s knowledge of the user gained by “observing” their activity. For example, Figure 4 shows the “Business Consultant (BC),” which is an intelligent agent built into the simulation that watches the student’s play and then offers helpful tips/questions based on that play based on the learner analytics and business intelligence processes. The goal of the BC is to provide the type of guidance to a student that a well-informed instructor would, thereby reducing (but not eliminating) the need for human experts to run the simulation. At the instructor's discretion, the BC agent is available to the students.

The goal of the BC agent is to assist in the student's learning. The BC's advice must be as relevant and current as possible. With that in mind, BC heavily references the student's User Rating to deliver advice that is accessible to the student at their current level of development. The number, detail, and level of helpfulness of the hints generated by the BC are directly impacted by the student's User Rating. This makes the BC agent adaptive on a mass scale to the status of the participants.

Figure 4: The Business Consultant

DISCUSSION

This paper introduces Empowerment Analytics, which is an architecture designed to provide information and feedback to students as a potential tool for enhancing student learning. Although we report two simple implementations as examples of our architecture, the significance of this architecture is multifaceted. Through automation, the architecture can be adapted to respond and react to students, thus improving student-content interaction while reducing the amount of interaction needed by the instructor to engage the student [1]. For example, currently the architecture is used to provide facts based on prior behavior, but imagine being able to provide, through personalized agents, individualized comments to students such as "I noticed you tend to perform better on quizzes when you watch the lectures before reading the chapter. You may want to consider watching the lectures before reading the chapters for future quizzes."

Ideally, an outcome from the architecture would be that the processes improve student skills and content knowledge. Although there is no statistical evidence at this time that the use of Empowerment Analytics improves student performance, the instructor of the Introduction to Management Information Systems course reported an increase in student activity after its use each week. Specifically, he saw an increase in accessing online lectures and in starting assignments after announcements were made regarding probability of finishing an assignment after starting the assignment after a certain number of days. The instructor of a Principles of Management course saw improvements in playing Micromatic when students used the Business Consultant to guide or aid in their decision making processes. Another outcome the Principles of Management instructor noted was the reduction in the number of emails and questions about how to engage with the Micromatic game. One of the major challenges in scaling up class size is the ability to give each student individualized attention and support. Empowerment Analytics has the potential to do just that. According to Anderson's Equivalency Theorem, "Deep and meaningful formal learning is supported as long as one of the three forms of interaction (student-teacher, student-student, or student-content) is at a high level. The other two may be offered at minimal levels, or even eliminated, without degrading the educational experience" [1, p. 4]. Thus, by improving student-content interaction, the Empowerment Analytics that we propose and illustrate in this paper can result in improved student learning as class sizes increase and as online learning increases.

CONCLUSIONS AND NEXT STEPS

This paper outlines and illustrates an architecture for the use of the transactional data that is available in learning management systems (LMSs) and some other virtual learning environments (VLEs) such as business simulation games. Effective use of transactional data can potentially increase student retention, especially when students are bombarded with large classes in their first few years of college level enrollment. Retaining students is concomitant with retaining a loyal customer — that is one seat that the admissions department does not have to identify a transfer student for replacement, thus saving the college or university significant dollars.

Empowerment Analytics continues to evolve. The goal of the architecture is to find and solve problems sooner than has been possible before and on a much larger scale. Having access to this information can modify the behavior of both the instructor and the students. Although we report how the architecture supports the instructor in the student-teacher engagement mode and how the automated feedback to students can enhance student-content interaction, we did not discuss in detail what the instructors can learn from the analysis and the possible next steps for the instructor to continuously improve the course. For example, it is easy to inform an instructor when a certain percentage of students did not perform well on a particular assignment and if the lack of performance was content-based or skill-based. For example, if an instructor assigns a writing assignment and the students did well with the actual answer but there were significant problems with grammar and punctuation, then the instructor is aware that the content was readily applied but poorly communicated through grammar and punctuation. If this is not a course that teaches grammar and punctuation, then the instructor has a choice of bringing a module on proper grammar and punctuation into the course content but not including the completion of the module in the hours required to complete the class, sending students to the Writing Center or any other options available. And if the opposite is true, that the problem was with the application of the content, then the instructor has to analyze his or her assumptions: Was the assignment clearly written and explained? Was enough time allotted to the learning activities that lead to the assignment?

Finally, there are the societal and ethical impacts of this technology that currently are unclear. Who should have access to this information? What are the privacy and security concerns? What are the implications to the students? What are the implications to advising? What are the implications to the instructor's evaluation and tenure? What are the implications to a program/college's accreditation efforts? Ferguson notes that one of the "future challenges" is to "develop and apply a clear set of ethical guidelines" because "no detailed ethical framework has been developed for learning analytics. This is a pressing need for the field" [6]. She identifies that the ethical framework would be used to make decisions about a variety of related issues: "ownership and stewardship of the data," "what rights learners have in relation to their data," "the extent to which [learners] have a responsibility to act on the recommendations supplied by learning analytics," how "to obtain informed and ongoing consent to the use of data," and how learners can "opt out" or "have their analytic record cleared." These are among the questions that will be considered as we continue development of Empowerment Analytics.

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