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Designing, Developing, and Implementing Real-Time Learning Analytics Student Dashboards

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Student Dashboards

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A dissertation submitted to the faculty of
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Doctor of Philosophy

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ABSTRACT

Designing, Developing, and Implementing Real-Time Learning Analytics
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This document is a multiple-article format dissertation that discusses the iterative design, development, and evaluation processes necessary to create high quality learning analytics dashboard systems. With the growth of online and blended learning environments, the amount of data that researchers and practitioners collect from learning experiences has also grown. The field of learning analytics is concerned with using this data to improve teaching and learning. Many learning analytics systems focus on instructors or administrators, but these tools fail to involve students in the data-driven decision-making process. Providing feedback to students and involving students in this decision-making process can increase intrinsic motivation and help students succeed in online and blended environments. To support online and blended teaching and learning, the focus of this document is student-facing learning analytics dashboards. The first article in this dissertation is a literature review on student-facing learning analytics reporting systems. This includes any system that tracks learning analytics data and reports it directly to students. The second article in this dissertation is a design and development research article that used a practice-centered approach to iteratively design and develop a real-time student-facing dashboard. The third article in this dissertation is a design-based research article focused on improving student use of learning analytics dashboard tools.

Keywords: feedback, charts, graphs, data processing, educational technology, courseware

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Most of all, I would like to acknowledge the support of my wife, Valerie, and my children, Annie and Bennett, who have allowed me to spend years of my life researching and writing as a scholar throughout my dissertation work.

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DESCRIPTION OF RESEARCH AGENDA AND DISSERTATION STRUCTURE

Online and blended learning are becoming increasingly common in higher education classrooms (Allen & Seaman, 2015). As students interact with resources in these blended and online environments they generate a stream of data that is often captured and stored. The field of learning analytics and educational data mining are concerned with using this data to improve teaching and learning (Baker & Inventado, 2014). The process for meaningfully using this data to improve teaching and learning includes a number of stages: capture, predict, act or report, and refine (Cambell, DeBlois, & Oblinger, 2007). The educational data mining community predominantly focuses on the prediction aspect of this process, while the learning analytics community predominantly focuses on the feedback or reporting aspects of the process. Within the learning analytics community, a commonly used reporting method is through a learning analytics dashboard (Verbert et al., 2014).

The majority of learning analytics dashboard tools have been developed to assist instructors or administrators (Schwendimann et al., 2017). While beneficial for instructors and administrators to accomplish their goals, these tools leave students out of the data-driven decision-making process. Student-facing tools, on the other hand, give students direct access to information, which in turn can lead to increased intrinsic motivation, positive reflection behaviors, and metacognitive skills (Verbert et al., 2014). These self-regulatory and metacognitive skills are the skills students need to succeed in online learning environments (Garrison, 2003). To support students in making data-driven decisions in online and blended learning environments, we have iteratively designed, developed, and implemented a student-facing learning analytics dashboard. After implementation, we discovered students did not use the dashboard tool as much as we thought they would. To increase student use of learner dashboards, we conducted a design-based research study investigating whether course structure changes, instructor practice changes, and dashboard design changes would influence student use.

Dissertation Structure

This dissertation, *Designing, Developing, and Implementing Real-Time Learning Analytics Student Dashboards*, is an article-format dissertation, which combines the nature of a regular dissertation format with three publishable articles.

The first pages of this dissertation satisfy the university and department requirements for dissertations and theses. Each article in this dissertation conforms to the style guide of the journal to which each article was or will be submitted.

Article 1 – Review of Research on Student-Facing Learning Analytics Dashboards and Educational Recommender Systems

In the first section, I present the first article of my dissertation, a literature review article, which was published (a preliminary version) in the P*roceedings of the Learning Analytics and Knowledge Conference* as well as (full version) in *Institute of Electrical and Electronics Engineers Transactions on Learning Technologies* (IEEE TLT). The style guide for IEEE TLT is a unique style guide to IEEE journals, so the article formatting will be very different from American Psychological Association (APA) formatting. The article is included as a prepublication version of the manuscript and was accepted in its current format.

For this article, we conducted a literature review on student-facing learning analytics reporting systems. In this review, we discovered that the majority of articles in the learning analytics dashboard (LAD) literature are still not well developed. Many of the authors of these systems reported on their work in conference proceedings and only around 15% of the authors conducted experimental research on their system. In addition, we found that while many authors describe the final system they used in their course, the authors do not report on the design process used to get to that final design. The main purpose for these systems was to increase student reflection and awareness, however, the majority of authors examined the effect of their systems on student achievement or behavior, not on student reflection or awareness. Another finding was that authors rarely report on or measure student use of their systems. This is important because if students are not using the system it invalidates any experimental evidence due to implementation fidelity issues. This article was the first of its kind as a systematic review of student-facing learning analytics reporting systems. However, research on open learner models (OLM) was not included due to missing keywords and search criteria. I am currently working with an international collaborative group to build on this review, researching the similarities and differences between learning analytics reporting system research and open learner model research, especially focusing on what each field can learn from the other.

Article 2 – The Design, Development, and Implementation of Student-Facing Learning Analytics Dashboards

In the second section, I present the second article of my dissertation, formatted in APA, with references included after the article. This article has been accepted to the *Journal of Computing in Higher Education*.

In this article, we discuss the iterative design and development of a student-facing dashboard using a practice-centered approach. In this article, we outlined the technical infrastructure necessary to track and report the data for a real-time dashboard system. Then, through an iterative, practice-centered approach, we designed and developed a content recommender dashboard and a skills recommender dashboard. The content recommender provides students with their current level of content mastery broken down at the concept level. It also provides video, practice questions, and web resource recommendations for concepts students struggle on. The skills recommender dashboard calculates a skill score for various skills and provides a student's scores next to the class average for comparison. Then the system provides recommendations for how the student can increase their various skill scores. We found that students do not use these dashboard tools as much as we thought. Despite not using the dashboards very much, student perceptions of the systems were generally high.

Article 3 – Increasing Student Use of a Chemistry Learner Dashboard Using a Design-Based Research Approach

The final article included in this dissertation is a design-based research article. Potential journals for this article include *The Journal of Research in Science Teaching* and *Computers and Education*. In the final article of this dissertation, we propose a design-based research approach to investigate which factors lead to increased student use of an online homework system dashboard. We will implement the dashboard system in three consecutive semesters of a general chemistry course at a large private US institution.

For the first iteration, we used surveys to understand student perceptions of the system and student click data within the dashboard to determine what we should change for the following semester. For the second iteration, we used student click data within the dashboard as well as additional methods to understand student use of the system unless we find similar results to previous semesters. For the third iteration, we used surveys to understand student perceptions of the system and student click data within the dashboard to see if the changes we made throughout the design-based research study were successful.

Throughout these three iterations, we made dashboard design, course structure, and instructor practice changes to influence the frequency with which students used the dashboard tools. Our metric of interest was student use of the dashboard. We measured student use in clicks per day, power user status (greater than 50 clicks in the dashboard), and user status (greater than zero clicks in the dashboard). We found that because of making changes to dashboard design, course structure, and instructor practice, student use of the dashboard system increased.

ARTICLE 1

Review of Research on Student-Facing Learning Analytics Dashboards and Educational Recommender Systems

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Note: this article conforms exactly to the IEEE TLT style guide. This is a prepublication version. It was accepted for publication and published in its current state. I am the lead author on the article, receiving help from Katrien Verbert, listed as second author of the manuscript. The reference for the article is:

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies*, *10*(4), 405-418.

Review of research on student-facing learning analytics dashboards and educational recommender systems

Robert Bodily and Katrien Verbert, *Member, IEEE*

Abstract—This article is a comprehensive literature review of student-facing learning analytics reporting systems that track learning analytics data and report it directly to students. This literature review builds on four previously conducted literature reviews in similar domains. Out of the 945 articles retrieved from databases and journals, 93 articles were included in the analysis. Articles were coded based on the following five categories: functionality, data sources, design analysis, student perceptions, and measured effects. Based on this review, we need research on learning analytics reporting systems that targets the design and development process of reporting systems, not only the final products. This design and development process includes needs analyses, visual design analyses, information selection justifications, and student perception surveys. In addition, experiments to determine the effect of these systems on student behavior, achievement, and skills are needed to add to the small existing body of evidence. Furthermore, experimental studies should include usability tests and methodologies to examine student use of these systems, as these factors may affect experimental findings. Finally, observational study methods, such as propensity score matching, should be used to increase student access to these systems but still rigorously measure experimental effects.

Index Terms—Data mining, Data and knowledge visualization, Self-assessment technologies, Homework support systems, Adaptive and intelligent educational systems, Literature review

1 INTRODUCTION

ONLINE learning continues to grow, in part, due to reduced costs, increased flexibility regarding class schedules, and improved mobility when taking classes (Allen & Seaman, 2014). As online learning becomes more widespread, it becomes increasingly important to understand how to help learners succeed in online environments. The focus of the emerging field of learning analytics is to achieve this goal. Learning analytics is defined as "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" (Siemens, 2010, para. 6). This definition is used because it was provided during the first conference on learning analytics and has since been adopted by the Society of Learning Analytics Research (SoLAR). The learning analytics process includes selecting, capturing, analyzing, and reporting data, and then refining this process based on what has been learned (Clow, 2012; Greller, & Drachsler, 2012). The majority of learning analytics systems report student interaction data to instructors or administrators (Schwendimann et al., 2016). However, these systems restrict student autonomy as administrators and instructors make decisions affecting student learning without direct student involvement. Student autonomy is defined within the self-determination theory framework as the level of control students are given in their learning. Students with high levels of autonomy are likely to be intrinsically motivated to succeed (Ryan & Deci, 2000). Student-facing learning analytics systems can enable student autonomy, giving students more control over their learning and helping them feel more intrinsically motivated to succeed. For this reason, the focus of this review is on student-facing learning analytics reporting systems.

In this paper, we first discuss previous literature reviews related to this topic and how our review builds upon their work. We then discuss the methodology for identifying and including articles in our review. Then, we report on the coding and analysis methodology. Finally, we discuss our findings, give recommendations, and provide implications for practice to improve online teaching and learning.

2 LITERATURE REVIEW

The scope of student-reporting systems would encompass all assessment and feedback systems in the literature and would be far too large for a single review. To narrow the focus, this literature review will focus exclusively on learning analytics systems that collect *click-level student data* and *report this data directly to students*. This data reporting may take the form of text feedback, recommendations, visualizations, or dashboards. These systems are found in a variety of educational technology fields such as intelligent tutoring systems, educational

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recommender systems, educational data mining systems, and learning analytics dashboard systems.

Intelligent tutoring systems are electronic systems which seek to improve learning that "must possess: (a) knowledge of the domain (expert model), (b) knowledge of the learner (student model), and (c) knowledge of teaching strategies (tutor)" (Hartley & Sleeman, 1973, p. 808). Educational recommender systems are defined as "any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options" (Burke, 2002, p. 1). Educational data mining systems "[seek] to use…data repositories to better understand learners and learning, and to develop computational approaches that combine data and theory to transform practice to benefit learners" (Romero & Ventura, 2010, p. 1). Learning analytics dashboards "support users in collecting personal information about various aspects of their life, behavior, habits, thoughts, and interest. [They also] help users to improve self-knowledge by providing tools for the r eview and analysis of their personal history" (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013, p. 2). A diagram illustrating the focus of this literature review is indicated with the student-facing systems gray oval seen below (Figure 1).

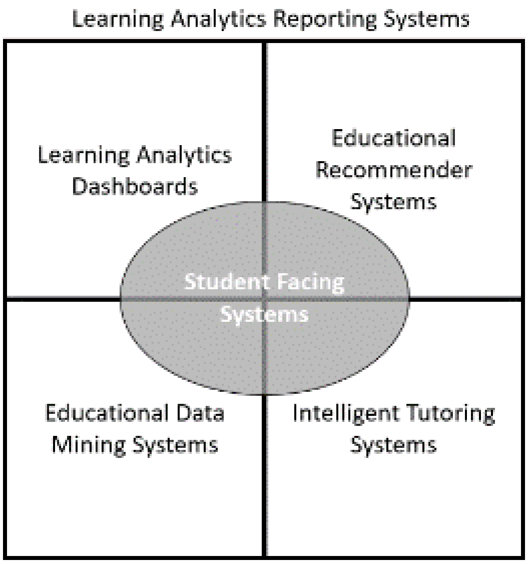

Fig. 1. A diagram illustrating the focus of this literature review situated between various educational technology sub-fields.

2.1 Previous Reviews

Four previously published literature reviews are relevant to this review. Verbert et al. (2013) reviewed 15 learning analytics dashboards (LAD). These LAD were selected for review in order to provide an illustration of their conceptual framework and provide interesting examples for the reader. Verbert et al. (2013) coded these articles based on the target user (e.g., instructor, student), what data was tracked (e.g., resources use, time spent), and what type of evaluation was conducted (e.g., usability, effectiveness). This categorization of LAD based on data type, target user, and evaluation conducted was the first published review of LAD, so instead of including a large number of articles, it provided an example for future research.

Verbert et al. (2014) built upon the work done in Verbert et al. (2013) by expanding the categorization of LAD and including additional LAD in the analysis. Their article is still not an exhaustive search of the literature, but instead seeks to provide a variety of interesting articles that will benefit the reader. Additional categories added to this analysis beyond the Verbert et al. (2013) article include devices used (e.g., laptop, cell phone, tabletop), some extra types of evaluation conducted (e.g., efficiency), and data tracking technology used (e.g., microphone, depth sensor, manual reporting). Additional systems were included in this analysis when compared with the previous study, but it still only included a small number of articles.

Yoo, Lee, Jo, and Park (2015) took 10 articles from the previous two literature reviews—Verbert et al. (2013) and Verbert et al. (2014)—and extended their framework by adding a more extensive evaluation criteria. They found that the current research on LAD is lacking in evaluation, so they created an evaluation framework of 11 sub-categories for dashboard evaluation: goal-orientation, information usefulness, visual effectiveness, appropriation of visual representation, user friendliness, understanding, reflection, learning motivation, behavioral change, performance improvement, and competency development. The sub-categories in the evaluation framework were excellent and were instrumental in the development of pieces of the categorization framework for this literature review.

Schwendimann, Boroujeni, Holzer, Gillet, and Dillenbourg (2016) conducted the first exhaustive search of the literature on LAD. Their methodology included searching for the phrases "dashboard AND ("learning analytics" OR "educational data mining" OR "educational datamining" in the databases ACM Digital Library, IEEE Xplore, Springer Link, Science Direct, and Wiley (Schwendimann et al., 2016, p. 1). Their search included all learning dashboards regardless of the stakeholder the system was intended for. They found that the majority of systems are instructor facing (74%) in a higher education context, and researchers do not conduct much research on the impact of these systems on teaching and learning.

We are interested in examining what types of systems exist in the student-facing learning analytics reporting system literature regarding their purpose, functionality, and types of data collected. Schwendimann et al. (2016) addressed this question at a broader level discussing the purpose, data sources, platforms, indicator types, visualization types, and technologies used. However, this analysis looked at each level separately, or at most, two levels at a time. We are interested more specifically in the mechanisms by which student-facing systems attempt to improve teaching and learning, which would require an analysis across categories. This has not previously been done, and would require a more comprehensive search of the literature beyond learning analytics dashboards (Schwendimann et al., 2016), along with a method and categorization scheme that allowed for comparison across codes. Schwendimann et al. (2016) suggested this was a gap in the current research and said, “The field still lacks comparative studies among different dashboards or dashboard design options” (p. 9). One of the first topics to address in order to compare dashboards or dashboard design options is to understand what types of systems exist in student-facing reporting literature based on their purpose, functionality, and data types collected.

We are also interested in examining which methods are being used to increase the rigor of student-facing reporting systems research. Verbert et al. (2013, 2014), Yoo et al. (2015), and Schwendimann et al. (2016) all partially addressed this question. However, these four previous reviews focused on summative evaluation of systems that had already been created. We are interested in both summative and formative evaluation, specifically looking for evaluation or research methods being used to increase the rigor of design and development in student-facing learning analytics reporting systems research.

Lastly, we are interested in examining, across the field, the effect of student-facing learning analytics reporting systems on student achievement, student behavior, and student skills. This has not been previously addressed in a literature review and would provide a synthesis of the effect of these systems on student behavior, achievement, and skills.

In summary, we will address the following questions in this review:

1. What types of systems exist within the student-facing learning analytics reporting system literature based on their purpose, functionality, and the types of data they collect?
2. Which methods are being used to increase the rigor of research in student-facing learning analytics reporting system literature?
3. What is the effect of having access to a student-facing learning analytics reporting system on student behavior, student achievement, and student skills?

3 Article Search Methods

Learning analytics reporting systems research is a multidisciplinary research area that is a combination of education and computer science. Because of this, the following education and computer science journal databases have been included in our search: ERIC to capture education articles, IEEE Xplore to capture computer science conference proceedings, Computers and Applied Sciences to capture computer science journal articles, and ACM to capture additional computer science articles. We also conducted targeted searches in Google Scholar, reviewed the entire educational data mining (EDM) and learning analytics and knowledge (LAK) conference proceedings, and found relevant literature reviews for additional citations to ensure articles were not missed because they were not indexed in the previously mentioned databases. The searches conducted are explained in Table 1.

TABLE 1
Databases, Journals, and Articles Searched with their Corresponding Topic or Search Term

Source	Search Term or Topic	Count
ERIC	(student OR students) AND ("data driven decision making" OR "resource use" OR analytics OR "student interaction” OR clickstream OR “online activity” OR "data mining") AND (dashboard OR visualization OR visual OR recommendation OR recommendations OR recommender)	193
LAK & EDM Proceedings	dashboard OR visualization OR visual OR recommendation OR recommender OR feedback	24
IEEE Xplore	(student OR students) AND (.QT.data driven decision making.QT. OR .QT.resource use.QT. OR analytics OR .QT.student interaction.QT. OR clickstream OR .QT.online activity.QT. OR .QT.data mining.QT.) AND (dashboard OR visualization OR visual OR recommendation OR recommendations OR recommender)	260
Computers and Applied Sciences	(student OR students) AND ("data driven decision making" OR "resource use" OR analytics OR "student interaction" OR clickstream OR "online activity" OR "data mining") AND (dashboard OR visualization OR visual OR recommendation OR recommendations OR recommender)	102
ACM database	(student OR students) AND ("data driven decision making" OR "resource use" OR analytics OR "student interaction" OR clickstream OR "online activity" OR "data mining") AND (dashboard OR visualization OR visual OR recommendation OR recommendations OR recommender)	172
Google Scholar: search 1	intitle:"feedback system" AND intitle:"learning"	66
Google Scholar: search 2	intitle:"learning analytics" AND intitle:"feedback"	9
Google Scholar: search 3	intitle:"learning dashboard" OR intitle:"learning analytics dashboard"	14
Google Scholar: search 4	intitle:"dashboard" AND intitle:"feedback"	8
Google Scholar: search 5	intitle:"learning analytics" AND (intitle:"reflection" OR intitle:"reflect")	7
Google Scholar: search 6	intitle:"learning analytics" AND intitle:"awareness"	6
Google Scholar: search 7	intitle:"data mining" AND (intitle:"recommendations" OR intitle:"recommendation" OR intitle:"recommend") AND intitle:"learning"	17
Drachsler, Verbert, Santos, & Manouselis, (2015)	Literature review on educational recommender systems	37
Romero & Ventura, 2010	Literature review on educational data mining	30
Verbert et al., 2013, 2014; Schwendimann et al., 2016	Literature reviews on learning analytics dashboards	20

We chose to only include journal articles that were peer reviewed and published between January 2005 and June 2016. The year 2005 was the start year because no articles were found before that time. The only exception to journal articles is conference proceedings from IEEE Xplore, the Learning Analytics and Knowledge conference, and the Educational Data Mining conference. IEEE Xplore is a database for computer science conference proceedings, so conference presentations within this database were included in our search. The learning analytics and educational data mining conference proceedings are the two conferences most closely related to learning analytics reporting systems, so they were included in this review as well.

To increase the rigor of our search criteria, literature review articles in similar domains were found and reviewed to identify relevant articles to this literature review. From this search, the following literature reviews were identified: an educational recommender system review article (Drachsler et al., 2015), an educational data mining review article (Romero & Ventura, 2010), and three learning analytics dashboards review articles (Verbert et al., 2013; Verbert et al., 2014; Schwendimann et al., 2016). We were not able to find any relevant articles from intelligent tutoring system review articles.

Finally, to ensure important articles were not missed, the titles of all of the previously found articles were examined for keywords. Keywords included learning dashboard, feedback system, recommendations, dashboard, learning analytics, feedback, reflection, and awareness. Once these words were identified, they were entered in Google Scholar and relevant articles were either kept as part of the review or rejected based on our inclusion criteria (see Table 1 for the exact searches). Once all articles had been identified, duplicates were removed because some articles showed up in multiple databases. There were 945 articles remaining for further analysis.

3.1 Inclusion Criteria

There were two main inclusion criteria used to narrow the pool of articles for this literature review. First, the article must have discussed a learning analytics system. This means the system had to automatically track student interaction data. For example, this data could be resource use, time spent data, or social interaction data. Furthermore, assessment data alone did not count. Second, the system must automatically report data directly to students. For example, this could be in the form of visualizations, text-based feedback, dashboards, or recommendations.

Articles that did not meet both of these two inclusion criteria were eliminated from the analysis. This narrowed the scope of this literature review to 93 articles. The list of articles included in this analysis can be viewed at the following web address www.bobbodily.com/article_list.

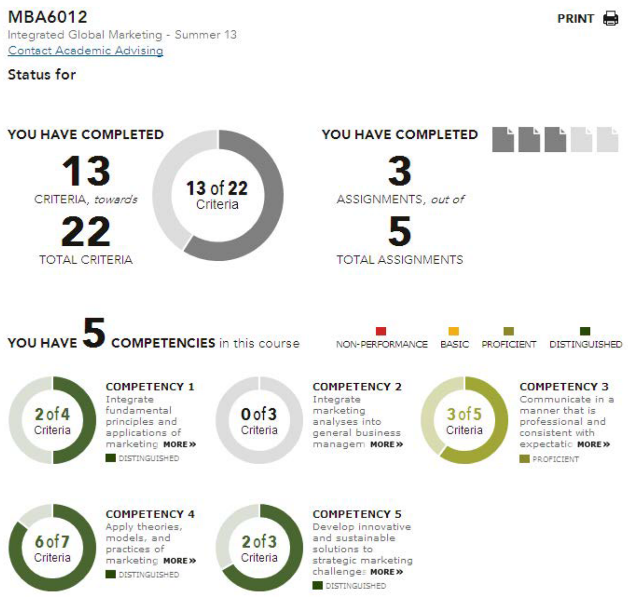

Fig. 2. J. Grann and D. Bushway, "Competency Map: Visualizing Student Learning to Promote Student Success," *Proc. Fourth Int'l Conf. Learning Analytics and Knowledge (LAK14)*, 2014; http://doi.org/10.1145/2567574.2567622. Figure 3.

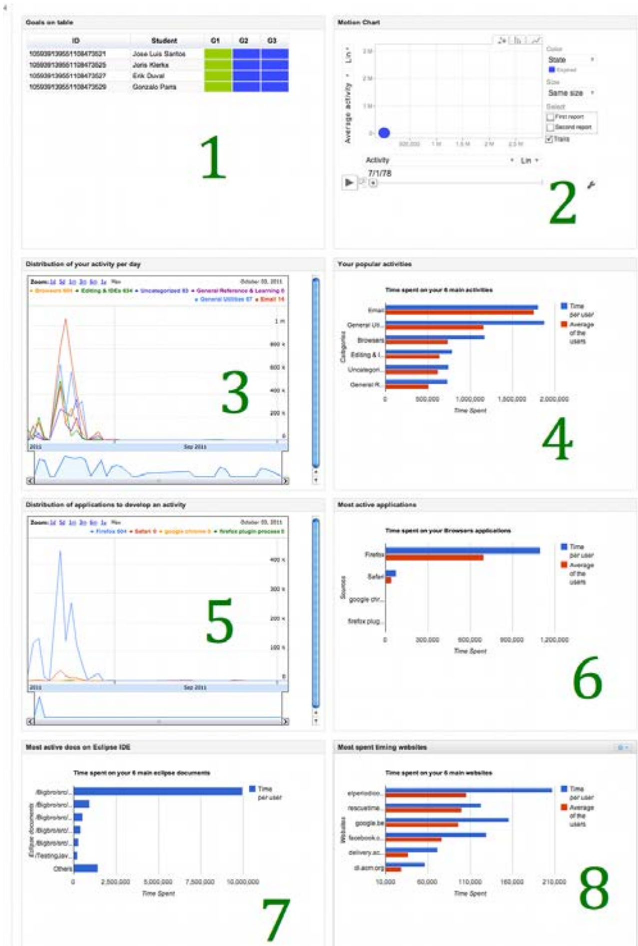

Fig. 3. J.L. Santos et al., "Goal-oriented visualizations of activity tracking: A case study with engineering students," *Proc. Second Int'l Conf. Learning Analytics and Knowledge (LAK12)*, 2012; http://doi.org/10.1145/2330601.2330639. Figure 5.

4 Category and Sub-Category Definitions

The 93 articles included in this analysis were coded based on the following five categories: functionality, data sources, design analysis, student perceptions, and measured effects. The functionality and data sources categories were used to determine the type of each system for our first research question, the design analysis and student perceptions categories were used to examine what kinds of methods are being used to increase the rigor of the design and development process of student-facing reporting systems for research question two, and the measured effects category will review the effect of having access to a learning analytics reporting system on student behavior, student achievement, and student skills for research question three. Each of these five categories was composed of subcategories. The categories and subcategories are defined below. These categories and subcategories were determined using both an open and closed coding approach. Some categories and subcategories were based on the coding categories used in previous literature reviews and some categories emerged as common themes from the articles in this review. We have included two learning analytics dashboards (see Figure 2 and 3) that provide multiple data views for students in order to provide a visual context for the categories and subcategories in this review (Santos et al., 2012; Grann & Bushway, 2014).

4.1 Functionality

The purpose of the functionality category is to determine what affordances the learning analytics reporting system offered to students and is broken down into the following subcategories: intended goal of the system, data mining, visuals, visual technique, recommendations, feedback, class comparison, and interactivity. These subcategories are defined in Table 2.

TABLE 2
SUB-CATEGORY DEFINITIONS FOR THE FUNCTIONALITY CATEGORY

Sub-category	Definition
Intended goal of the system	The goal that the system was attempting to achieve
Data mining	Any automated statistical process before data reporting
Visual	Reported data to students in a visual or graphical form
Visual technique	The visualization method used to display data
Recommendations	Told students to do something based on the data
Feedback	Provided text feedback to students
Class comparison	Allowed students to compare their data with other students data
Interactive	Allowed students to interact with the reporting system

4.2 Data Sources

The data sources category examines the inputs to the learning analytics reporting systems to determine what types of data are being collected, analyzed, and reported to students. This category is broken down into the following subcategories: resource use, assessment, social interaction, time spent, other sensors, and manually reported data. These subcategories are defined in Table 3.

TABLE 3
SUB-CATEGORY DEFINITIONS FOR THE DATA SOURCES CATEGORY

Sub-category	Definition
Resource use	The number of times a resource was accessed
Assessment	Student mastery data as measured by assessment
Social interaction	Any activity performed interacting with others
Time spent	The amount of time spent accessing resources
Other sensors	Other sensors include mouse tracking, heartrate, steps, etc.
Manually reported	Data manually reported by student, instructor, or other party.

4.3 Design Analysis

The design analysis category examines the design considerations that should be made before testing or implementing a reporting system with students in an actual class. The design analysis framework we use in this paper includes four sub-categories: needs assessment, information selection, visual design, and usability test. These sub-categories are defined in Table 4.

TABLE 4
SUB-CATEGORY DEFINITIONS FOR THE DESIGN ANALYSIS CATEGORY

Sub-category	Definition
Needs analysis	Analysis conducted to determine the needs of an end-user
Information selection	Justification provided for the types of data collected
Visual design	Justification provided for the types of visualizations used
Usability testing	Conducted a system usability test beyond student perceptions

4.4 Student Perceptions

The student perceptions category groups a variety of student perceptions on learning analytics reporting systems into the following subcategories: usability, satisfaction/usefulness, perceived behavior change, perceived achievement change, and perceived skills change. These sub-categories are defined in Table 5.

TABLE 5
SUB-CATEGORY DEFINITIONS FOR THE STUDENT PERCEPTIONS CATEGORY

Sub-category	Definition
Usability	Asked students about the usability of the system
Usefulness	Asked students about the usefulness of the system
Perceived behavior change	Asked students if they perceived any behavior changes
Perceived achievement change	Asked students if they perceived any achievement changes
Perceived skills change	Asked students if they perceived any skills changes (e.g. meta-cognition, self-regulation, etc.)

4.5 Measured Effects

The measured effects category deals with articles that conducted a research experiment to determine what effect the learning analytics reporting system had on students. The measured effects category is broken down into three subcategories: behavior, achievement, and skills. Each of these sub-categories is defined in Table 6.

TABLE 6
SUB-CATEGORY DEFINITIONS FOR THE MEASURED EFFECTS CATEGORY

Sub-category	Definition
Behavior	Conducted an experiment to determine if the system had an effect on student behavior
Achievement	Conducted an experiment to determine if the system had an effect on student achievement
Skills	Conducted an experiment to determine if the system had an effect on student skills (e.g. meta-cognition, self-regulation, etc.)

4.6 Student Use

The student use category deals with articles that track student data, report this data back to students, and then track how students interact with or use the reporting system. This interaction could be in the form of clicks, online sessions in the system, or page views in the system.

5 RESEARCH METHODS

A researcher examined the methods, results, discussion, and conclusion section of each article to determine whether the article would receive a one or zero in each of the categories (except visualization type and intended goal of the system which received a text description). Every article received either a one (indicating the article included the subcategory topic) or a zero (indicating the article did not include the subcategory topic). None of the subcategories within these five categories were mutually exclusive, which means an article could receive a one on every subcategory within every category. In order to ensure an objective coding approach, 20% of the articles were coded by a second reviewer. The agreement between the two coders was 86%.

In order to determine the types of systems that were discussed in the final set of articles, the functionality and data sources categories were grouped together to identify patterns across categories. Then, the number of unique article types was counted based on the data sources and functionality sub-category codes.

To determine what methods were being used to increase the rigor of student-facing learning analytics reporting systems, we used an open coding approach. Some category ideas were taken from previous literature reviews but the final categories emerged throughout the process as we read and coded articles.

To report on the effects of giving students access to these systems on student behavior, achievement, and skills, each article that was coded as having done experimental research was analyzed again in more detail. The sample size, research methodology, and results for each article were extracted and summaries were provided for each sub-category.

6 Results and Discussion

The results from analyzing each coding category will be discussed in the following sections, organized based on our research questions. First, we provide an overview of the frequency counts and percentages of total for each sub-category (see Table 7). Then, we discuss the results for each research question. Please note that the sub-category names have been extended or slightly modified to provide a better description for the context of the table.

TABLE 7
Frequency Counts and Percentages of Total for Each Sub-category in Our Analysis

Category	Sub-category	# of Articles	% of Articles
Data Sources	Resource use data	70	75%
Functionality	Visualizations	62	67%
Functionality	Data mining	46	49%
Functionality	Recommendations	43	46%
Functionality	Class comparison	35	38%
Data Sources	Assessment data	34	37%
Student Perceptions	Student perceptions on usefulness	34	37%
Data Sources	Social interaction data	32	34%
Student Perceptions	Student perception on usability	32	34%
Functionality	Interactive	29	31%
Data Sources	Time spent data	28	30%
Functionality	Text feedback	17	18%
Actual Effects	Actual effect on student behavior	17	18%
Student Perceptions	Behavior change	16	17%
Actual Effects	Actual effect on student achievement	16	17%
Student Perceptions	Skills change	15	16%
Design Analysis	Justification for data selection	14	15%
Data Sources	Manual reporting data	12	13%
Design Analysis	Conducted a visual design analysis	12	13%
Student Use	Tracked student use of system	12	13%
Design Analysis	Conducted a usability test	10	11%
Data Sources	Other sensor data	7	8%
Design Analysis	Conducted a needs assessment	6	6%
Student Perceptions	Achievement change	2	2%
Actual Effects	Actual effect on student skills	2	2%

The most prevalent system characteristics were tracking resource use data, reporting data in visualizations, using data mining to process data, and providing recommendations to students. The least prevalent system characteristics were tracking other sensor data, conducting a needs assessment to identify the needs of the system end-user, asking students if they perceived an achievement change based on their system use, and examining the effect of these systems on student skills (e.g., awareness, meta-cognition, motivation, etc.).

6.1 Types of Learning Analytics Reporting System

The results presented in this section specifically address our first research question: What types of systems exist within student-facing learning analytics reporting system literature based on their purpose, functionality, and the data types they collect? We aggregated the co-occurrence of various functionality and data sources categories in order to identify patterns in the types of student-facing learning analytics reporting systems discussed in the articles in this review. The groupings for the functionality category are reported in Table 8 below. A *visualization* type means data was displayed visually in a graphic or dashboard (Few, 2013). If it is an *enhanced visualization* type it means the visualization included a class comparison feature or an interactivity feature. If it is a recommender system or includes recommendations it means it is a *recommendations* or *recommender system* type. If data mining was conducted on the data before it was reported to students it is included as a *data mining* type.

TABLE 8
Types of Student-facing Learning Analytics Reporting Systems as Categorized by Functionality

Type of reporting system	# of articles	% of articles
Enhanced visualization	27	29%
Data mining recommender system	25	27%
Enhanced visualization with recommendations	8	9%
Visualization	6	6%
Visualization with recommendations and data mining	6	6%
Other	22	23%

The most prevalent systems were the enhanced visualizations and the data mining recommender systems. This makes sense because enhanced visualizations would come from the learning analytics dashboard literature and the data mining recommender systems would come from the educational recommender systems literature.

One example of an enhanced visualization tool is a learning analytics dashboard that provides students with their mastery level on each concept in the class. The dashboard also provides class comparison functionality and interactivity. This means users can compare themselves to their class by looking at a visual representation of data generated in the class. One example of a data mining recommender system is a resource recommender that uses collaborative filtering techniques to recommend resources to a student based on their similarity to other students.

The groupings for the data sources category are reported in Table 9. The most common data source combinations are included, and the least common data source combinations are grouped into the “other” category. The most common data source collected was social interaction and resource use (17% of articles). All of

TABLE 9

TYPES OF STUDENT-FACING LEARNING ANALYTICS REPORTING SYSTEMS AS CATEGORIZED BY DATA SOURCES

Type of reporting system	# of articles	% of articles
Social interaction and resource use	16	17%
Resource use, time spent, and assessment data	9	10%
Resource use and assessment data	8	9%
Social interaction data	8	9%
Social interaction, time spent, and resource use data	6	6%
Resource use and time spent	6	6%
Other	40	43%

the data sources within the top six categories collected some combination of social interaction, resource use, time spent, and assessment data.

To look for more detailed patterns, the two categories were combined and we searched for trends across all of the sub-categories within these two categories. The top three types of reporting systems as categorized by data sources and functionality are displayed in Table 10. The rest of the system types are not displayed because there were two or less occurrences.

TABLE 10

TYPES OF REPORTING SYSTEMS AS CATEGORIZED BY DATA SOURCES AND FUNCTIONALITY

Types of reporting systems	# of articles	% of articles
Social interaction, resource use, data mining, recommendations	9	10%
Social interaction, resource use, enhanced visualization	6	6%
Social interaction, resource use, assessment data, data mining, recommendations	4	4%
Other	74	80%

There were two examples of learning analytics reporting systems that merit additional discussion from the Other category. The first is called The NTU Student Dashboard (Ferguson, Sharkey, & Mirriahi, 2016). The NTU Dashboard was implemented at Nottingham Trent University. This system integrates tutor comments, student biographical information, door swipes (tracked by student ID card), library loans, virtual learning environment use, Dropbox submissions, and attendance in classes. This comprehensive data collection contains much more information than Learning Management System data and could potentially increase the predictive power of current early-alert warning system prediction algorithms. However, there are not published results yet from this dashboard on the effect of the dashboard on student behavior, achievement, or skills.

The other example of a system in the Other Sensors category was an educational resources recommendation system (Holanda et al., 2012). This system provided students with blog article recommendations based on a blog web crawler, student post behavior, and student post content on instructor blogs. This article included a text mining component not common among other learning analytics reporting systems. In a small experimental study, they found that interacting with the resource recommender increased the percentage of interaction by 83.3% (N=12). More research is needed on learning analytics reporting systems that incorporate text mining as additional data sources to see the effect on student achievement, behavior, and skills.

There are no major trends across reporting systems. When combining the sub-categories for the functionality and data sources categories, there were 68 unique types of systems. One reason for this could be that student-facing learning analytics reporting systems are tools that are context dependent. Each circumstance has unique instructors, students, needs, and goals, which means each system needs to track unique data sources and report it in unique ways to strive to achieve a unique goal. Another reason for this could be that researchers do not know what is best to track and report to students, so there are a wide variety of approaches in use. In summary, more research should investigate which types of data and functionality elements lead to increased student success to help guide the student reporting system field.

6.2 Methods for Rigorous Research

The results presented in this section specifically address our second research question: Which methods are being used to increase the rigor of research in student-facing learning analytics reporting system literature? The methods identified using an open coding approach in the article analysis stage include the following methods: needs assessment, information selection analysis, visual design analysis, student usability perceptions, conducting usability tests, and tracking student use of the reporting system. Each of these sub-categories along with examples extracted from the literature will be discussed in the following sections.

6.2.1 Needs Assessment

A needs assessment is common in instructional design. The purpose is to understand what the stakeholder or end user needs. It answers the question, "What problem needs to be solved?" Out of the 93 total articles in this analysis, only 6% of articles (N=6) included a description of their needs analysis. It is likely that an informal needs assessment is still happening for some of the other 87 articles included in our analysis; however, it is important to be more explicit about the kinds of needs analyses we are conducting. Santos, Verbert, Govaerts, & Duval (2013) conducted a needs assessment on their system called StepUp!. They conducted three brainstorm sessions with different groups of students to identify problems students faced in their courses. Next, each student group rated the previously identified problems to determine which were most important to them. The problems that could be addressed by a learning dashboard were then selected and sorted based on student ranking of importance. Solutions to the final list of problems were then implemented into the learning dashboard. We need more research on learning analytics reporting systems that conduct rigorous needs assessments.

6.2.2 Information Selection

The learning analytics process definition commonly includes a data selection stage (Campbell & Oblinger, 2007). The data selection stage is determining what data should be collected. In our analysis, we call this the information selection sub-category. Only 15% of articles (N=14) provided information about why they were collecting certain types of data. It is likely that there are good reasons the rest of the articles are collecting the types of data they are collecting; however, it would be beneficial if researchers started examining why they are collecting some types of data but not other types of data.

From the articles in this literature review, we have identified three articles that conducted a meaningful information selection process. In order to identify performance indicators, Ott, Robins, Haden, & Shephard (2015) reviewed the literature that examined predictors of student success in programming courses. Then, they created indicators that had been previously shown to predict student success to use in their models. These indicators include pre-course grades, number of submitted laboratory tasks, time of submission, and mid-semester exam result. These indicators were then visualized in the infographic they created for their course (Ott et al., 2015).

Feild (2015) conducted exploratory data analysis in order to determine which indicators were worth reporting to students as feedback. The author analyzed various levels of data including days of the semester, days of the week, hours of the day, and start and submit times of student assignments. Based on their findings in the exploratory data analysis, Feild identified four messages they could include in their feedback engine (Feild, 2015).

Iandoli, Quinto, De Liddo, and Buckingham Shum (2014) used a theoretical framework in order to determine what feedback to give to students. The three categories of feedback they identified were community (who), interaction process (how), and knowledge absorption (what, where). Based on the purposes identified for each of these categories, they were better able to frame what, when, and where to represent information to students (Iandoli et al., 2014). Based on this analysis, more learning analytics reporting systems should report on reviewing previous literature, conducting exploratory data analysis, and using a theoretical framework to guide the information selection process.

6.2.3 Visual Design

For learning analytics dashboards, this would be deciding which visualization is the best representation of the data. For educational recommender systems, this would be deciding when and where is best to provide a recommendation. Olmos & Corrin (2012) provide an excellent example of the benefits of an iterative design process when designing the visual component of a learning analytics reporting system. The first visualization they tried was a table. Then, after reflecting on the advantages and disadvantages of their table design, they tried a Gantt chart. After additional reflection, their next iteration used a line chart which was more vertically compact and showed additional information not found in the Gantt chart. After a final round of reflection, their final design expanded on the line chart by adding additional symbols as markers along the lines as well as color coding the lines based on student. While this process was devoid of any kind of user-testing, this iterative visual design process allowed them to create a much cleaner, succinct, and informative visualization than they would have been able to create otherwise. More learning analytics reporting systems need to take into account and report on the visual design process in order to improve the visualizations in these systems.

6.2.4 Student Perceptions of Usability

The majority of these articles administered surveys to students to assess student perceptions of usability. This can apply to learning analytics dashboards as well as educational recommender systems. In a recommendation system, the questions might include if the recommendations were presented at an appropriate time or if the recommendations were easy to understand. In a dashboard system, the questions might include if the visualizations were easy to understand or whether they were easy to access. To better analyze student perceptions beyond administering a survey, Wise, Zhao, & Hausknecht (2014) conducted interviews with seven students and the instructor to evaluate the usability of their system. These interviews focused on student understanding of and reactions to the system analytics. One of the benefits to using interviews instead of surveys to assess usability is participants can be led through a think-aloud process to give feedback as they interact with the system. This interview process can provide additional insights into the usability of a system than a single response on a survey (Wise et al., 2014). More learning analytics reporting systems should include interviews and think-aloud protocols in their usability testing in addition to survey work.

6.2.5 Usability Testing

This is separate from the student perceptions usability category (discussed in the student perceptions category section above) because usability testing has to be more rigorous than simply asking students if they thought the system was user-friendly or easy to use. The usability test subcategory included usability tests such as: (1) an assessment on how easily students could find information in the system, (2) an assignment to see whether students could accomplish tasks within the system, or (3) a validated system usability survey (Brooke, 1996). Only 11% of articles (N=10) included a report on a usability test.

Two methods of conducting a usability test were selected that merit further discussion. Santos, Verbert, & Duval (2012) and Santos, Govaerts, Verbert, & Duval (2012) both used the System Usability Scale (SUS) to assess the usability of their system. One of the benefits of using this scale is it has been previously used by hundreds of other research papers evaluating online systems, so it allows systems to be compared on an equal scale. Santos, Boticario, and Perez-Marin (2014) conducted the most rigorous usability assessment and brought in a usability and accessibility expert to evaluate their system. The usability expert interviewed faculty to determine how they were using the system as well as students to see how they were using the system. The expert also evaluated the learning system environment as well as student interactions within the learning environment. With help from the usability expert, the authors were able to (1) enhance the learning management system for "adaptive navigation support", (2) semantically model course recommendations, (3) create recommendations and configure services in the learning space, (4) prepare data collection methods, and (5) assess the learning experience based on the data collected. In future reporting system research, a system usability scale, evaluation expert, or other appropriate methods should be used to improve system evaluation.

6.2.6 Student Use

This category was not discussed in previous literature reviews (Verbert et al., 2013; Verbert et al., 2014; Schwendimann et al., 2016; Yoo et al., 2015), but has important implications for research on the effect of reporting systems on student behavior, achievement, and skills. If students are not using the system, the results about the effects of the system on students are not meaningful. Furthermore, the way in which students use these systems can provide valuable information to guide future research and development of reporting systems. Research on student-facing reporting systems should address this by tracking the frequency and duration of student use as students interact with the visualizations, recommendations, or feedback provided in reporting systems

6.3 Measured Effects

The results presented in this section specifically address our third research question: What is the effect of having access to a student-facing learning analytics reporting system on student behavior, student achievement, and student skills? Out of 93 articles in this analysis, 16% of the articles (N=15) examined the effect of their system on student behavior; 15% of the articles (N=14) examined the effect of their system on student achievement; and 3% of the articles (N=2) examined the effect of their system on student skills. The effects found by these articles are summarized in Table 11, Table 12, and Table 13.

Table 11 summarizes the articles that examined the effect of a reporting system on student behavior. Three articles did not include sample sizes, seven articles had sample sizes less than 75 students, and five articles had sample sizes greater than 75. Randomized control trials and descriptive statistics were the predominant methods used to identify if students' behavior had changed.

TABLE 11

ARTICLE SUMMARIES INCLUDED IN THE MEASURED EFFECTS CATEGORY FOR BEHAVIOR CHANGE

Citation	Sample Size	Context	Result
(Hsu, 2008)	Not listed	Used association rule mining in an ESL student nursing course	21% of students accepted the system recommendation to view additional content
(Grann & Bushway, 2014)	Not listed	Used logistic regression to predict if use of competency map increased reregistration behaviors (controlling for student engagement)	Competency map behavior accounts for 7% additional variance beyond student engagement variables in predicting reregistration behavior
(Arnold, Hall, Street, Lafayette, & Pistilli, 2012)	about 8,000	Used descriptive statistics and chi-square comparisons between students that take and do not take course signals courses.	Students that participated in course signals courses were more likely to continue taking classes than those that did not enroll in course signals courses
(Xu & Makos, 2015)	73 students	Correlation and ANOVA analyses conducted to determine effect of student activation of a notification tool on collaboration behaviors	Students that enabled notifications (on 2 out of 3 systems) showed increased contributions in the social network space
(Nakahara, Yaegashi, Hisamatsu, & Yamauchi, 2005)	9 treatment, 53 control	Non-parametric mean difference testing was used to determine the effect of i-tree on student online social activity	Students in the i-tree treatment group visited the discussion space more frequently than those that did not have i-tree, however, they did not post more frequently.
(Wise et al., 2014)	9 students	Descriptive statistics were used to examine changes in student behavior over time.	After the analytics reporting was introduced, the percentage of posts viewed increased for all students (except 2 that were already at 100%). Some students had week by week changes based on personal goals, but there were few sustained changes due to the analytics reporting in this study
(Chen, Chang, & Wang, 2008)	27 treatment, 27 control	Descriptive group comparisons as well as t-tests were used to determine what effect having mobile access to learning awareness modules has on student learning behavior	The number of students completing assignments increased and LMS use increased when comparing treatment and control groups
(Lee, 2005)	15 control, 10 experiment	One-way ANOVA was used to determine what group differences exist between treatment and control in terms of web search activity.	Students that used their system, VisSearch, we able to better search the web when compared with students using traditional search engines; this is defined as reading more unique web pages, creating more bookmarks, extending more bookmarks, having an increased length of average search query, and revisiting web pages.
(Beheshitha, Hatala, Gašević, & Joksimović, 2016)	169 students	Hierarchical linear mixed models were used to determine the effect of access to data visualizations on the quantity and quality of discussion board posts taking into account their goal orientation	On two of the three visualizations, students post quantity increased; on the third student post quantity decreased. This was also seen with post quality as measured by discourse features.
(Huang, Huang, Wang, & Hwang, 2009)	57 treatment, 56 control	A Markov chain model and an entropy-based approach were used to see if the recommender system could provide helpful learning paths to students	Almost 50% of students accepted recommendations from the recommender system.
(Vesin, Klašnja-Milićević, Ivanović, & Budimac, 2013)	35 treatment, 35 control	T-test were used for mean difference testing to determine whether Protus, an adaptive and personalized recommendation engine, had an effect on student learning.	Students in the treatment group were able to complete assignments more quickly and were able to complete the entire course more quickly than students in the control group.
(Holanda et al., 2012)	12 students	Descriptive statistics were used before and after initial discussion posting to see what effect recommendations had on posting behavior	There was an 83.3% student interaction increase after recommendations were given.
(Santos et al., 2014)	173 students	T-tests were used to compare treatment and control groups to determine the effect of recommendations on student resource use	Students that received recommendations logged in more frequently, completed their coursework more quickly, completed more questions, and answered more questions correctly on assignments than students in the control group.
(Janssen et al., 2007)	410 treatment, 398 control	T-tests were used to compare how quickly learners were able to finish the course	There were no significant differences between the treatment and control groups in terms of learning efficiency
(Kuosa et al., 2016)	Not listed	Descriptive statistics were used to compare treatment and control groups to determine the effect of their visualizations on student behavior.	Students in the treatment group were able to find correct answers more quickly and were able to more quickly pick keywords to search on.

Results on the effectiveness of these systems is mixed. Future research should consider quasi-experimental methods to provide all students with the reporting tool and still evaluate effectiveness; use larger sample sizes; and continue to examine the effect of reporting systems on student behavior.

TABLE 12

ARTICLE SUMMARIES INCLUDED IN THE MEASURED EFFECTS ACHIEVEMENT CHANGE CATEGORY

Citation	Sample Size	Context	Result
(Grann & Bushway, 2014)	Not listed	Mean difference testing was used to determine whether students that used the competency map had higher levels of performance than students that did not	Students that used the competency map had slightly higher achievement rates, however, this was not statistically significant
(Arnold et al., 2012)	about 8,000	By comparing student achievement before and after course signals, descriptive statistics were used to determine the effect on student achievement.	Classes with course signals (compared with the same course before course signals) saw increased A's and B's and decreased C's, D's, and E's.
(Park & Jo, 2015)	36 treatment, 37 control	A randomized control trial research design was used to determine the effect of the LAPA dashboard on student achievement. Mean difference testing was used to determine if there was a significant difference between groups.	Although the treatment group had slightly higher achievement rates than the control group, there were no significant differences between the treatment and control group regarding their achievement rates.
(Kim, Jo, & Park, 2015)	72 treatment, 79 control	A randomized control trial research design was used to determine the effect of the learning dashboard on student achievement. Mean difference testing was used to determine if there was a significant difference between groups.	The treatment group (received access to dashboard) had significant higher achievement rates on the final exam than the control group.
(Denley, 2014)	about 50,000 students	Descriptive statistics were used to compare students in Degree Compass courses to those not enrolled in Degree Compass courses.	Compared with previous students that did not use Degree Compass, students that used Degree Compass received more passing grades (A, B, or C), especially if the student belonged to an at risk population. The prediction algorithm accuracy was 90%.
(Ott et al., 2015)	512 students	T-tests were used to determine if there was a significant achievement difference between previous semesters without the infographic and later semesters with the infographic. Assessments did not change between years and course curriculum stayed the same.	There was no significant difference after the introduction of the class infographic on student achievement.
(Dodge, Whitmer, & Frazee, 2015)	442 treatment, 440 control	T-tests to compare treatment and control groups of a randomized control trial were used to determine the effect of trigger events (recommendation emails) on student achievement.	There was no significant difference between treatment and control groups in terms of achievement. However, in one course there was a significant treatment effect on pell eligible students. This effect was not seen in the other course included in this study.
(Chen et al., 2008)	27 treatment, 27 control	T-tests were used to compare treatment and control groups to determine the effect of the ubiquitous learning website as well as the device used (cell phone, laptop, PDA) on student achievement and learning goal achievement.	Use of the ubiquitous learning website had significant effects on "testing results, task-accomplished rate, and learning-goal-achieved rate" (Chen et al., 2008, p. 90).
(Saul & Wuttke, 2014)	about 80 students	Comparisons were made between students that used the askMe! system and the students that did not use the system.	The average grade of students that used the system was higher than those that did not. In addition, the failure rate was four times lower for those that used the system when compared with those that did not.
(Beheshitha et al., 2016)	about 100 students	Controlling for achievement goal orientation, what effect do learning analytics visualizations have on the quality of student social media posts? A linear mixed-effects analysis was conducted.	The frequency and quality of student posts were affected positively and negatively, depending on the visualization.
(Huang et al., 2009)	57 treatment, 56 control	A Markov chain model and an entropy-based approach were used to see if the recommender system could provide helpful learning paths to students.	Learners in the treatment group performed significantly better than the control group on the evaluation system task.
(Vesin et al., 2013)	35 treatment, 35 control	T-test were used for mean difference testing to determine whether Protus, an adaptive and personalized recommendation engine, had an effect on student learning.	Student learning efficiency was improved, but no analyses were conducted to determine change in grade based on treatment effect.
(Santos et al., 2014)	173 students	T-tests were used to compare treatment and control groups to determine the effect of recommendations on student achievement	There were no significant differences between the treatment and control groups in terms of learning achievement
(Wang, 2008)	40 treatment, 40 control	A t-test was used to determine the effect of content recommendations on student exam score.	The treatment group performed equivalently to the control group on the pre-test, and then the treatment group had significantly higher scores than the control group on the post-test.

Table 12 summarizes the articles that reported on assessing the effect of reporting systems on student achievement. One article did not report sample size, three articles had sample sizes below 75, and ten articles had sample sizes greater than 75. These sample sizes were larger, on average, than those in the behavior change category. In addition, more articles used randomized control trials to determine student achievement differences when compared with behavior differences articles. Despite larger sample sizes and more rigorous methods, the results are mixed. Some studies showed benefits, some studies showed detrimental effects, and some studies showed both benefits and detrimental effects. Future research should use large sample sizes, continue to use randomized control trials or preferably quasi-experimental methods, and continue to examine the effect of reporting systems on student achievement.

Table 13 summarizes the two articles that examined the effect of a reporting system on student skills. Both articles found differences in student skills, the first in self-awareness and the second in interest. Due to the lack of research in this area, more research is needed on how reporting systems affect student motivation, interest, self-regulation, awareness, or self-efficacy.

TABLE 13

ARTICLE SUMMARIES INCLUDED IN THE MEASURED EFFECTS CHANGE IN SKILLS CATEGORY

Citation	Sample Size	Context	Result
(Kerly, Ellis, & Bull, 2008)	30 students	A randomized control trial and t-test analysis were used to determine whether using a chatbot with the CALM system had an effect on student learning	All participants became more aware of their own knowledge, but the treatment group (with chatbot) had a significant increase in self-awareness accuracy above that of the control group.
(Muldner et al., 2015)	209 students	Excitement and interest surveys were used before and after to establish a pre and post baseline. In addition, a one question excitement and interest question was used about every 10 minutes to gauge in the moment student affect. T-tests were used with groups split randomly to determine the effect of the student progress page on student affect.	Female students reported higher interest when they had the choice to use the student progress page, whereas male students reported higher interest when student progress page usage was enforced with a notification.

7 LIMITATIONS

One of the major limitations to this analysis is there is not a common vocabulary for learning analytics reporting systems (Van Barneveld, Arnold, & Campbell, 2012). As evidence, articles from educational recommender system literature, intelligent tutoring system literature, educational data mining system literature, and learning analytics dashboard literature were all included in this review. Because there are so many different keywords associated with these systems, there may be articles that were not included in our analysis that should have been. However, to address this limitation, we made our methodology especially rigorous in an effort to include as many relevant articles as possible. For example, we included education and computer science journals, we used various broad keywords in our initial search to catch as many articles as possible, we conducted targeted Google Scholar searches based on keywords we saw from our initial search, and we found related literature reviews to try to include as many relevant articles as possible.

Another limitation to this analysis is we limited our search to research articles, conference proceedings, or book chapters that discussed learning analytics reporting systems. There are undoubtedly many learning analytics systems that have not been researched or written about. These systems are not included in this analysis. However, we feel that the most effective learning analytics reporting systems will be empirically tested for their effectiveness, so we are satisfied with the inclusion criteria for this article.

The final limitation we address is the potential for subjectivity in the coding process because all of the articles in this analysis were coded by human researchers on a number of categories and subcategories. To mitigate this, 20% of the articles were randomly chosen and double coded by a second reviewer. The two reviewers had an 86% agreement.

8 Recommendations for Practice and Future Research

The results discussed previously have direct implications in practice and for future research. We first discuss considerations for those developing learning analytics reporting systems and then discuss future research topics.

8.1 Considerations for Practice

When starting to create a student-facing learning analytics reporting system, it is important to consider the questions listed below to guide the development process (Table 14). These questions correspond to categories discussed in previous literature reviews and form the outline for the categories discussed in this review. The importance of these questions and categories has been discussed in the results and discussion section.

TABLE 14
QUESTIONS TO GUIDE THE PROCESS OF CREATING A STUDENT-FACING LEARNING ANALYTICS REPORTING SYSTEM

Question	Category	% of Articles
What is the intended goal of the system?	Intended Goal	100
What visual techniques will best represent your data?	Visualizations	13
What types of data support your goal?	Information Selection	15
What do students need? Does it align with your goal?	Needs Assessment	6
Is the system easy and intuitive to use?	Usability Test	11
Why use the visual techniques you have chosen?	Visual Design	13
How do students perceive the reporting system?	Student Perceptions	17
What is the effect on student behavior/achievement?	Actual Effects	18
How are students using the system? How often? Why?	Student Use	13

In addition to considering these questions in the development of a learning analytics reporting system, it is also important to include justification for the questions found in Table 14 in the reporting of results. The number of articles that included answers to the questions above was less than 20% in all cases except intended goal of the system, which could be inferred from the article regardless if it was explicitly stated. The creators of these systems were likely thinking about and answering these questions, but the majority failed to report the results in their written work. The field of student-facing learning analytics reporting systems will be greatly improved by addressing and reporting on the questions listed above.

Another important consideration for practice is while many educational technology products have student-facing reporting systems, such as learning management system analytics tools, online homework system dashboards, or cognitive tutor reports, many of these systems do not conduct any research on their system. This means that their system might look well-presented, but that does not mean it has been empirically proven to help students. As instructors or administrators, you should question the claims of these systems unless they have evidence from research to support their claims.

The final consideration for practice deals with student use of reporting tools. From the student use category, 13% of articles reported on tracking student use of their system. In general, the articles reported low student use, around 30% of students access systems on average. However, systems that sent notifications to students through email or text had higher use than static systems students had to visit themselves. As an instructor or administrator, you should consider how to increase student use of these reporting tools. Factors to consider include student familiarity with the system, use of notifications and reminders, student perceptions of usefulness, and effectiveness of the system.

8.2 Recommendations for Future Research

Because student-facing learning analytics reporting systems is an emerging research field, there are many areas of future research. These topics will be addressed corresponding to categories evaluated in this review.

8.2.1 Student Use

The articles that reported on student use, on average, reported low use of their systems. Because of this, more research should be conducted to examine how to increase student use of these tools, specifically in supporting students to act on the feedback they receive in these reporting systems. In addition, more articles should track and report on the way in which students are using reporting systems. Additional research should be conducted to understand student help seeking behavior in online environments in order to support student motivation in engaging with learning analytics reporting systems.

8.2.2 Actual Effects

Based on the low number of articles evaluating the actual effects of these systems on students, more research is needed examining the effect of these systems on student behavior, achievement, or skills. In the actual effects tables (Table 11, 12, & 13), the results are mixed, and therefore not sufficient to make a conclusion about the effect certain types of systems have on student behavior, achievement or skills. In order to add additional rigor to this area of research, (1) larger sample sizes should be used for greater statistical power and the ability to make generalizations beyond the current sample, (2) more detail should be provided (see Table 14) about the reporting system to understand what features are causing the changes to students, and (3) random controlled trials or quasi experimental studies should be used to identify true effects in the place of correlation analyses or simple descriptive statistics comparisons. While these results may seem intuitive, many researchers are not using these methods. For example, none of the articles included in this analysis used an observational study to measure impact, such as propensity score matching.

8.2.3 Intended Purpose

It is interesting to note that while the most common purpose of these systems was to increase student awareness and reflection (N=35), only 2% of the articles (N=2) conducted an experiment to determine the effectiveness of the system on student skills (e.g., student reflection, awareness). It is also interesting that the majority of these student-facing systems are not trying to directly increase student retention or improve student engagement. Instead, they focus on student reflection or awareness. In future research, authors should be explicit about the purpose of their system, and should make sure their research questions and analyses align with that purpose.

However, it is possible that many of these systems were used by instructors as a part of mandatory activities in classes with the primary purpose of increasing student awareness and reflection. Student retention would then be less important as higher-level thinking and learning become the focus. If this is the case, researchers and practitioners should consider conducting research on what effect these tools have on student reflection and awareness.

One reason conducting rigorous research on learning technologies in the classroom is a challenge is because it requires a multi-disciplinary effort. Technically savvy team members must come together with researchers and teachers in order to create an appropriate research design, collect the data, analyze the data, and write up the results.

8.2.4 Student Perceptions

Based on the low article count in the student perceptions category, more research is needed to examine student perceptions of these systems and on the perceived effects of these systems on student behavior, student achievement, and student skills. This is important because a perceived effect on student behavior, achievement, or skills could lead to an actual effect on student behavior, achievement, or skills, similar to a pygmalian effect (Rosenthal & Jacobson, 1968). Student perceptions are also important to how students use these systems because as student perceptions improve about a system, they are more likely to use it.

8.2.5 Recommendations

There are two important pieces to a learning analytics reporting system: (1) helping students understand what has happened (through feedback or visualizations) and (2) helping students know what to do because of what they know (through recommendations). To see how many systems are currently doing both of these things, we examined the number of articles that had a recommendations component and a feedback or visualization component. Only 17% of articles (N=16) met these requirements. Future systems should address both what to tell the students to do in recommendations and why students should act on the information in text feedback or visualizations.

8.2.6 Usability

Many of the systems in this review failed to conduct a usability test. This is detrimental to the research field of learning analytics reporting systems because a lack of usability could be the reason why students do not like or use a system. More learning analytics reporting systems need rigorous usability tests conducted, either by administering a standard system usability survey, conducting think-aloud interviews with students, or bringing in a usability expert to evaluate the system. Once a system has been sufficiently evaluated from a usability perspective, additional questions such as what effect systems have on students can then be addressed.

8.2.7 Interactive/Exploration

We hypothesize that interactive or exploratory features in a learning analytics reporting system will lead to increased student use. Only a few articles included an interactive visualization component. Ji, Michel, Lavoue, and George (2014) created an excellent example of an interactive student dashboard called DDART. While they discuss other dashboards that allow dashboard customization, DDART is the first customizable dashboard that does not require computer programming experience in the visualization creation. The authors' dashboard, DDART, allowed students to select parameters, create new indicators, and choose their own visualization method. They provided a graphical interface for students to use to remove the need for computer programming experience. Allowing students to select their own parameters, create their own indicators, and choose their own visualizations may increase student motivation to use the dashboard as they would be more invested in the experience. This level of customization might also increase student awareness or self-reflection because students would have to decide which indicators and visualizations to create. Additional research should examine the effect of various types of dashboard interactivity on student behavior, achievement, and skills.

9 CONCLUSION

This article is a comprehensive literature review on learning analytics reporting systems that track student click-level data and report that data directly to students. In this analysis, we have discussed the types of student-facing learning analytics reporting systems based on system functionality and data sources collected, the methods used to increase the rigor of reporting systems, and the current findings of the effect of these systems on student behavior, achievement, and skills. Future research should focus not only on evaluating the final product of a reporting system, but also on evaluating the design and development process. This process includes administering a needs assessment, providing justification for information selection, justifying the visual design used, and conducting a usability test. More research is also needed with large sample sizes and rigorous experimental methods to examine the perceived and actual effects of learning analytics reporting systems on student behavior, student achievement, and student skills. There were not any articles in this review that used observational studies. Quasi-experimental methods, such as propensity score matching, should be used in observational studies to allow all students to have access to these systems and still conduct rigorous impact studies. If the goal of a system is to improve student awareness or reflection, the focus of the experimental study should be on student skills, giving a validated pre- and post-survey to determine differences. Student use of reporting systems is not well studied nor understood. Practitioners and researchers should track student use of these systems to understand how to support student motivation to improve the effectiveness of these student-facing learning analytics reporting systems.

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ARTICLE 2

The Design, Development, and Implementation of Student-Facing Learning Analytics Dashboards

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Abstract

We have designed, developed, and implemented a student-facing learning analytics dashboard in order to support students as they learn in online environments. There are two separate dashboards in our system: a content recommender dashboard and a skills recommender dashboard. The content recommender helps students identify gaps in their content knowledge; the skills recommender helps students improve their metacognitive strategies. We discuss the technical requirements needed to develop a real-time student dashboard as well as report our inquiry into the functionality students want in a dashboard. The dashboards were evaluated with focus groups and a perceptions survey. Students were positive in their perceptions of the dashboards and 79% of the students that used the dashboards found them user-friendly, engaging, useful, and informative. One challenge encountered was low student use of the dashboard. Only 25% of students used the dashboard multiple times, despite favorable student perceptions of the dashboard. Additional research should examine how to motivate and support students to engage with dashboard feedback in online environments.

Keywords: learning analytics; data visualization; student reporting tools; learning dashboards; iterative design; dashboard

The Design, Development, and Implementation of Student-Facing Learning Analytics Dashboards

In 2013 there were over five million online learners; this number continues to grow each year (Allen & Seaman, 2015). As the use of online learning continues to increase throughout higher education, there is a need for effective instructional strategies and tools to help students succeed in online environments. Online environments often do not have the same support structure as face-to-face classes and lack many of the motivating social aspects of a classroom environment. Because of this, online students need greater levels of support in order to be successful (Bekele, 2010; Jones & Issroff, 2007).

One attempt at providing support for students in online environments is through instructor-facing dashboard systems. Because instructors are generally blind to how students interact with online course materials, these instructor-facing systems provide instructors with information regarding student mastery and resource use so instructors can intervene with struggling students. The majority of dashboard systems are currently instructor-facing (Schwendimann et al., 2017) and fail to directly support learners in improving their learning skills, such as metacognition and self-regulation. Learners need these skills to successfully navigate online courses (Garrison, 2003).

One promising research field focused on achieving the goal of helping students develop metacognition and self-regulation is the field of learning analytics. Learning analytics (LA) is commonly defined as “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” (Siemens, 2010, para. 6). LA can be used to track and report student-content interactions in meaningful ways to support students in learning. The reporting stage of LA (Elias, 2011; Greller & Drachsler, 2012), or providing feedback to students to increase metacognitive and self-regulatory strategies, is commonly achieved through a learning analytics dashboard (LAD). An LAD visualizes information in a way that allows the end user to quickly make sense of data at a glance (Few, 2013). Real-time LADs can be provided to students to increase student awareness of their own knowledge and to help students reflect on their learning in order to become better learners (Verbert et al., 2014).

Learning analytics dashboards have many advantages over other feedback systems: the system collects data unobtrusively and does not interfere with student engagement in the course, the system automatically collects data without external intervention from instructors or course designers, and the system can output data reports to inform students of their progress and behaviors in a course in real-time.

In order to better support student learning in online environments, we have iteratively designed and developed a real-time student dashboard. Our content dashboard provides content recommendations to help increase student metacognition as well as remediate student knowledge gaps. Our skill dashboard provides skill recommendations to help students become better learners. While many articles discussing LADs exist, most articles do not report on the entire design and development process from start to finish. We build on the current body of knowledge by reporting on the technical infrastructure needed to facilitate a real-time dashboard, the iterative design process we used to design our dashboards, and a final feature review process conducted with surveys and focus groups. Beyond reporting on the entire design and development, we also build on current LAD research by selecting what data points we would like to capture, reporting data in real-time, evaluating our recommendations and data representations to determine what changes should be made to continuously improve our dashboard, and tracking student use of our dashboards.

Literature Review

In the following literature review we discuss the theoretical importance of learning dashboards, review the current state of student-facing LAD research, identify gaps in the current body of knowledge, and discuss how we have grounded our work in what has already been done.

Theoretical Foundations

Self-determination theory (SDT) as presented by Ryan and Deci (2000) provides a good framework through which to view learning analytics dashboards. Self-determination theory provides guidance for which conditions support autonomy, competence, and relatedness. Within the student-facing learning analytics dashboard context, we focus on autonomy and competence. As students interact with educational technology tools, they want to be efficient and effective in their work. In order to be intrinsically motivated, according to SDT, students should feel autonomous and competent. Student-facing learning dashboards, as optional feedback tools, support student autonomy in allowing students to identify and remediate their knowledge gaps at their own time and pace. Dashboards also provide students with resources directly related to their knowledge gaps as well as opportunities to see progress in their learning mastery, potentially leading to increased levels of competence. As students feel competent and autonomous interacting with learning dashboards, we believe students will be more intrinsically motivated to succeed in their coursework, which will result in changes in behavior and increases in student achievement.

Student-Facing LAD Research

It is common for student-facing reporting systems to include either recommendations or visualizations, but not as common to include recommendations and visualizations within the same system. Visualizations or text feedback tell the user what has happened and provide justification for future action (Few, 2006). Recommendations provide action items that users can see on the screen to immediately act in a specific way based on what they have seen (Resnick & Varian, 1997). In Bodily and Verbert (2017), the authors found sixty-two student-facing dashboard articles. Of the systems discussed in those articles, only thirteen included both visualizations and recommendations (e.g., Anaya, Luque, & Peinado, 2016; Ott, Robins, Haden, & Shephard, 2015). Because of the theoretical benefits of including both recommendations and visualizations in a student-facing dashboard system (Resnick & Varian, 1997; Few, 2006), we continue the best practice of including both aspects in our system.

LADs commonly track students as they interact with resources throughout a course. However, LADs rarely track click-level student use of the dashboard tool (Verbert et al., 2014). This is important because whether students use the dashboard or not can impact the results of the evaluation or implementation of a dashboard system. Bodily and Verbert (2017) found that nine systems out of the sixty-three student-facing LADs in their study tracked student use of the dashboard system. Because of the importance of tracking students as they interact with an LAD, we have implemented an analytics system in our dashboard to track student use of our LAD.

Most articles discussing LADs discuss the final design and the evaluation process, but many leave out the design and development process that went into creating the dashboard. Bodily and Verbert (2017) found that ten systems out of the sixty-three student-facing LADs in their study provided justifications for the visual design chosen and the information selection process. Being transparent about the iterative design and development process that occurs before the final product could increase robust research on LAD (Santos, Govaerts, Verbert, & Duval, 2013), decrease LAD development time, and increase LAD effectiveness. This adds to the current body of the literature on LADs and should be included in every article (Bodily & Verbert, 2017). To justify our final design, we report on the entire design and development process in this article.

LAD functionality varies from static reports to fully dynamic visualizations that can be customized and explored by students. This interactivity allows for a simple interface that can be understood at a glance (Few, 2006) while still providing additional information to students who want it. Bodily and Verbert (2017) found that fifteen out of the sixty-three student dashboard articles they found discussed systems that had both class comparison and dashboard interactivity features. These features are generally desirable in an LAD, so we have implemented both class comparison as well as interactivity features in our LAD.

There are a number of data sources that LADs collect, but the most common data types are resource use, time spent, and assessment data. Despite these data types being the most common, most LADs do not collect all three. Bodily and Verbert (2017) found that of the sixty-three student dashboards in their study, ten dashboards collected all three types of data. Collecting multiple types of data to determine which is best to present to students is an important research topic in the field of learner dashboards (Verbert et al. 2013), so to extend upon the work of these dashboards, we also track and report on all three data types: time spent, resource use, and assessment data.

While there are a number of LADs that include each of the features discussed in this section, the system described in this article is the first to include all of them: providing recommendations and visualizations in the dashboard; tracking students as they use the dashboard; reporting on the design and development process of the dashboard in the article; providing class comparison as well as interactivity features; and tracking resource use, time spent, and assessment data.

We build on the work of others in the LAD research field by providing an additional context in which to study LADs. We have developed two real-time learning analytics dashboards that provide visualizations of student activity *and* provide recommendations for students to support them as they learn online. We also investigate student perceptions of our dashboards using focus groups and surveys, and we provide data on how students used the LAD throughout the course. The purpose of this research paper is to explore the LAD design process through the lens of the following questions:

1. What technical requirements are needed for an online learning system to collect and provide students with personalized information in a real-time student dashboard?
2. How should the dashboard be visually represented?
3. What functionality do students want in a dashboard?
4. How do students perceive the dashboards we have developed?

In the remainder of this paper, we discuss the following items: (1) the technical infrastructure needed to enable click-level data collection and real-time reporting; (2) the iterative design process we used to develop the dashboards; (3) the focus groups we conducted to investigate student perceptions of our dashboards; and (4) the dashboard perception survey to understand student perceptions of our dashboards.

Technical Infrastructure

In order to develop a LAD, it is necessary to collect click-level student data, store that data in a secure place, and have real-time access to that data. Unfortunately, most online systems do not collect and provide access to this kind of data. For example, most learning management systems (LMSs) were not designed to collect clickstream analytics data or provide real-time access to that data. While they have some analytics capabilities, there are three challenges associated with using built-in LMS analytics: (1) a lot of learning occurs outside LMSs that is not tracked within LMSs; (2) most LMSs have API limits that prevent real-time analysis and

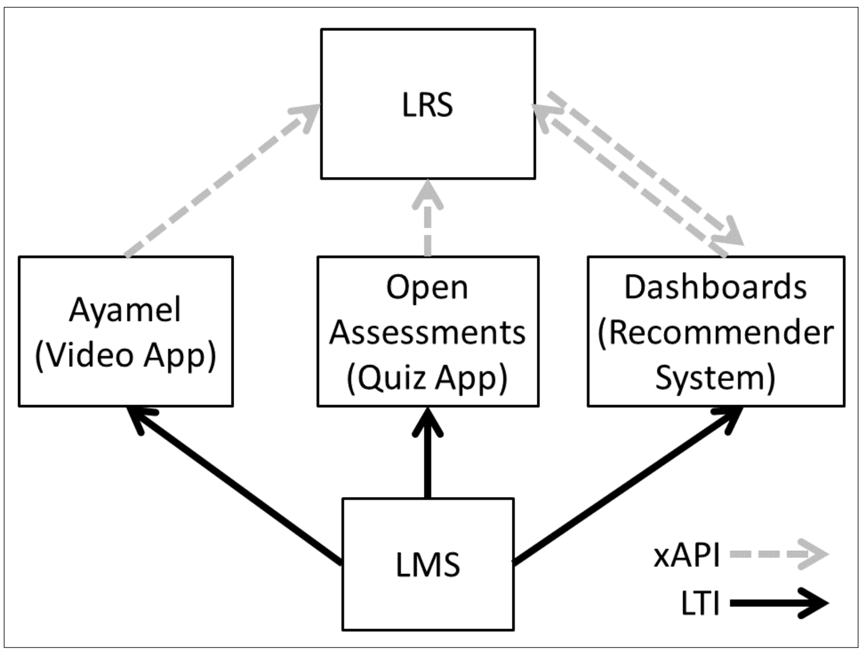

Figure 1. A diagram of our open analytics system.

reporting with large groups of students; and (3) LMSs do not collect click-level analytics as students interact with content on a page. In addition, many proprietary systems do not collect or report this kind of data either. To circumvent these problems, we have developed a learning analytics system that collects and reports student data in real-time (see Figure 1). We next discuss the technical details of our system.

Technical Definitions

1. Experience API (xAPI): A data format standard that allows multiple applications to collect and send data in a similar format for easy data access and aggregation (https://www.adlnet.gov/adl-research/performance-tracking-analysis/experience-api/).
2. Learning Tools Interoperability (LTI): A learning tool specification that facilitates single-sign-on access within educational applications (https://www.imsglobal.org/activity/learning-tools-interoperability).
3. Learning Record Store (LRS): A database that stores xAPI statements sent from different learning applications (http://tincanapi.com/learning-record-store/).

Our Learning Analytics System

Our system consists of four main applications: (1) a quiz application, (2) a video application, (3) a database, and (4) our dashboards. The *quiz application* is our own version of the open source assessment tool Open Embedded Assessments (openassessments.org). We used an updated version of the tool because it was LTI compliant. We then developed an xAPI backend to enable data collection within the quiz application. We chose these standards because they allowed us to overcome challenges with collecting data within LMSs and have been widely adopted (Santos et al., 2015). The *video application* was developed at a private institution in the United States, and we worked with them to implement xAPI in their analytics backend. This allowed us to track all events as students interacted with videos. Our dashboards are also LTI compliant, so students can access our dashboards from an LMS without logging in to our system. In addition, our dashboards are xAPI compliant, which means we are tracking all student interactions within our dashboards in addition to the video and quiz data. For our database, we used an open-source LRS called Learning Locker (https://learninglocker.net/). This database stored all of the student click events that occur within quizzes, videos, or our dashboards. Our student dashboards connect directly to the database, which enabled the dashboards to report student data in real-time. This means that every time a student reloads the dashboard they will have the most up-to-date information.

The metrics collected and calculated from data generated by students using applications in our learning analytics system are reported in Table 1.

Table 1

Data Points Collected or Calculated in our Analytics System

Video Analytics	Quiz Analytics	Dashboard Analytics
# of plays	# of question attempts	# of dashboard views
# of pauses	Time spent on quizzes	Time spent in dashboard
# of video seeks	# of quizzes attempted	# of video suggestion clicks
# of play rate changes	Average confidence level	# of quiz suggestion clicks
Average video speed	Max number of attempts	# of unique visits to dashboard
# of volume changes	Max time on a quiz	
Average volume setting	Score on quiz	
# of mute/unmute		
Number of max/minimize		
Time spent on videos		
Number of videos watched		

Designing the Real-Time Learning Analytics Dashboard

We have designed and developed two different student dashboards: a content recommender and a skills recommender. The content recommender system uses assessment data to give feedback to students on how to improve their mastery of each concept. This real-time feedback helps students to do better in their courses (Bangert-Drowns, Kulik, Kulik, & Morgan, 1991). Furthermore, students can easily identify where they should focus their studies to improve on weaker concepts, due to the metacognitive benefits of a system like this (Hacker, Dunlosky, & Graesser, 1998). This is particularly useful in preparation for an exam. The skill recommender system uses online interaction data to calculate a score for student skills (time management, knowledge awareness, consistency, persistence, deep learning, and online activity). The system then provides feedback to students on how to increase their skill scores. This “self-knowledge has many benefits, such as fostering insight, increasing self-control, and promoting positive behavior” (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013, p. 2).

Design Theory and Framework

Instead of choosing a design framework or a specific set of learning theories to guide the design and development of our dashboards, we used a practice-centered approach (Wilson, 2013). A practice-centered approach differs from more theoretical instructional design strategies because, instead of focusing on one specific theory or line of thinking, designers take a more eclectic approach and use learning theories and instructional strategies they believe will improve student learning based on their experience in practice. Despite being eclectic in nature, this approach does not lack rigor. A practice-centered approach is based on practice theory (Huizing & Cavanagh, 2011) and is broken down into five main concepts: exercising agency, tensions in the system, integrating human values, reconciling differences, and sharing practices.

With the exercising agency concept, Wilson (2013) posits that often designers rigidly constrain themselves to instructional theories or practices that inhibit them from making the biggest practical impact. Being thoughtfully eclectic allows a designer to make adjustments they feel are needed based on their practical experience and agency. The tensions in the system concept illustrates that “dynamic system modeling can better accommodate the complexity found in practice. Each part can potentially affect any other part of the system, and the goal is finding a compatible balance or harmony between elements that is sustainable over time” (Wilson, 2013, p. 9). Integrating human values discusses the practical need to help humans solve stakeholder problems. In our case, this means helping students succeed in online courses through the use of an LAD. Reconciling differences means learning from failure and thinking empathetically. Wilson (2013) further argued, "The goal of a practice approach would be to expand our views to accommodate both activity- and experienced-based studies of how people connect and relate to each other in the design of and activity of learning and instruction" (p. 14). The last benefit of a practice-centered approach is sharing practices: "Reverse engineering (carefully analyzing successful practice in case-study fashion) can highlight elements of [good] designs in use that would be used in future designs" (Wilson, 2013, p. 15).

A practice-centered approach fits with the design of a learning dashboard because our goal is very practice-centric: to increase student use of the dashboards and increase the effectiveness of the dashboards.

Content Recommender

We used a practice-centered, iterative design process to design the two student-facing dashboards. The content recommender went through three iterative design phases; the skills recommender went through two iterative design phases. We first discuss the three design phases for the content recommender.

Phase 1. The content recommender was designed to help students identify their knowledge gaps and provide recommendations to fill those knowledge gaps. This functionality aligns well with the goals of students in the class. For example, students want to easily and quickly find resources to help them learn, know what they need to study, and recognize what they already know.

Because students have multiple attempts per problem, we penalize a correct score if they click "show answer" beforehand or attempt a problem multiple times. Attempting a problem multiple times can lead to a correct answer even when the material has not been mastered. As attempts increase, the probability of a correct answer without mastery increases (Millman, 1989). The *mastery score* is defined by the formula below. However, if the calculated score is less than zero, the score is set to zero.

$$\frac{\#\ of\ correct\ responses}{total\ \#\ of\ questions} - \frac{\#\ of\ show\ answer\ before\ correct}{total\ \#\ of\ questions} - \sum \frac{\#\ of\ attempts\ per\ question - 1}{\#\ of\ question\ options - 1}$$

This means that if a student clicks to see the answer before getting it right, the score on the question will be zero for the mastery score calculation. In addition, if a student takes four attempts on a problem with four question options, they will also receive a zero for the mastery score calculation. It also means a student could get 100% on the quiz for their grade, but their mastery score would still be zero if they clicked “show answer” every time or used all of their attempts for every question. This mastery score calculation is similar to existing grading implementations in other systems with multiple attempts (Kortemeyer, 2015; Doorn, Janssen, & O’Brien, 2010).

Once the mastery score was calculated, we decided to visualize it in a horizontal bar chart (see Figure 2).

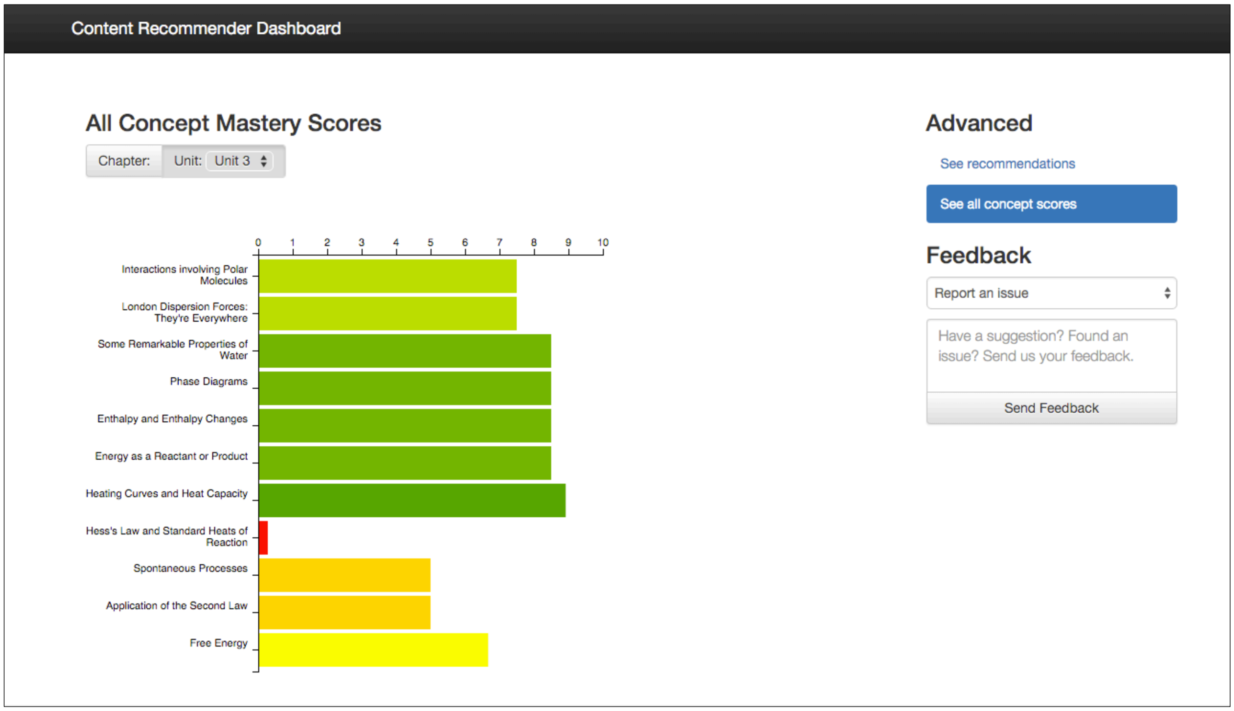

Figure 2. The concept scores view of the content recommender version one.

This allowed students to filter the concepts in the class based on which concepts would be covered in each exam in order to easily see where they are struggling in the course. This formative unit-level feedback is especially helpful in helping students diagnose where they should focus their efforts when preparing for exams (Shute, 2008). We also made each bar in the bar chart clickable so we could provide recommendations to the student based on their online activity with quizzes and videos. The distance that the bar extends across the screen corresponds with an increasing mastery score. In addition, green indicates a higher mastery score while red indicates a lower mastery score.

The recommendations view (see Figure 3) is where students go if they clicked on the mastery bar chart.

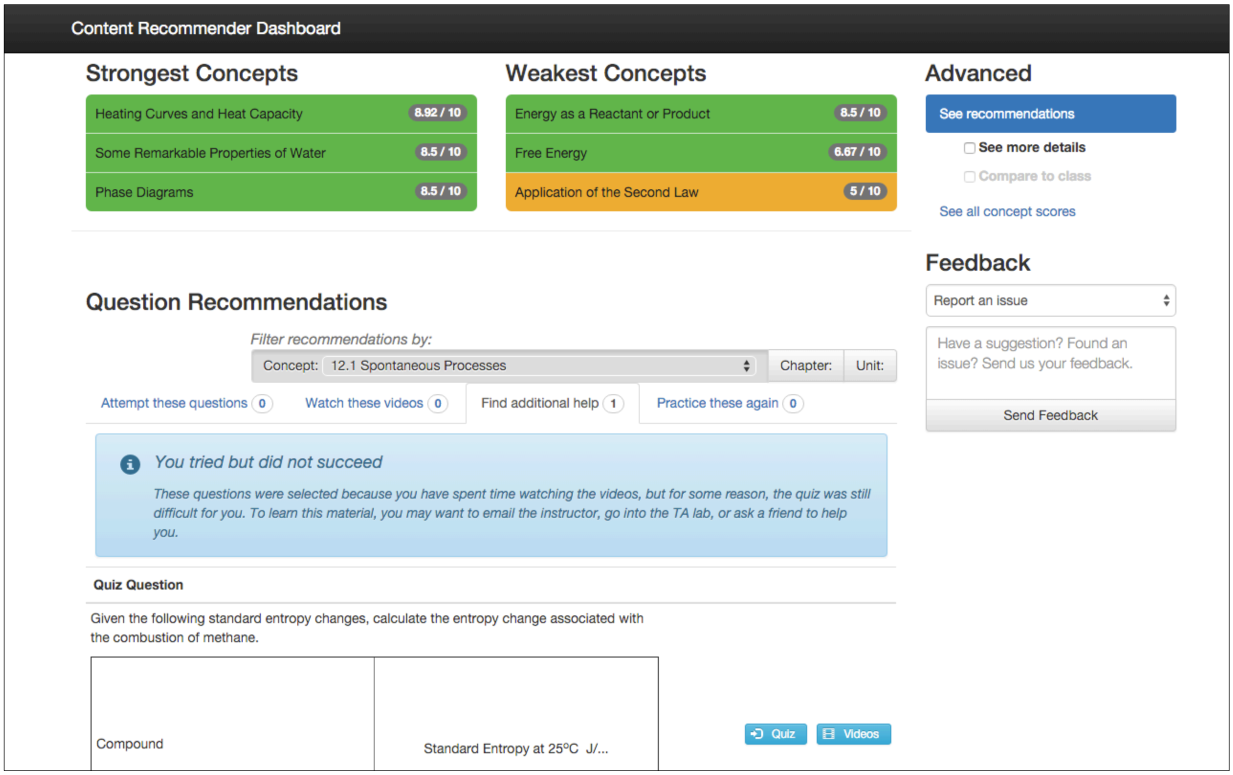

Figure 3. The recommendations view of the content recommender version one.

Initially, we used simple rule-based recommendations, but the system is designed to allow for more sophisticated recommendations. The recommendations were divided into four different groups: (1) low video use, low mastery score; (2) high video use, low mastery score; (3) no question attempts; and (4) eventually correct with many attempts. Each group had its own set of respective recommendations: (1) watch the videos related to the concept you are struggling with, (2) study with a friend or teaching assistant because the videos were not helping you succeed, (3) attempt the questions you have not answered yet, and (4) retry these problems for practice. These recommendations were determined based on the reason a student may have been located in each quadrant. For example, a student with low video use and a low mastery score could reasonably be expected to improve if they watched the content videos. However, a student with high video use and low mastery score needs additional help from a teaching assistant or friend because they were not able to figure out the material on their own with the videos. Quiz question and video links were provided next to the recommendations panel so students could easily click to follow the recommendation.

The main purpose of a dashboard is to be easily understood "at a glance" (Few, 2006), so, to simplify our dashboard, we provided students with a strongest concepts box and a weakest concepts box at the top of the screen. We also provided students with an advanced toolbar in the upper-right-hand corner of the screen to allow students to toggle certain features to explore the data more in depth. Providing a simple and advanced view for technical and non-technical audiences has previously been successful in Danado, Davies, Ricca, and Fensel (2010) and Rydberg (2011).

After developing version one of the content recommender, we informally evaluated our dashboard with students and faculty in our department (N=10). This evaluation focused on whether the dashboard was user-friendly and useful for students. We specifically focused on how students could act based on the information received from the dashboard. Based on this initial evaluation, we discovered a range of weaknesses associated with our design:

1. With two separate screens, it is hard to see recommendations and get an overview of where you are struggling at the same time.
2. The advanced toolbar on the right side is not intuitive.
3. The recommendations view has a simple and advanced view, but it ended up being too complicated and cluttered in both views.
4. Students cannot see how their video watching is affecting their mastery scores.
5. Small concept titles are hard to see because the bar and the title have to take up space across the screen.

We also discovered a number of strengths to our design:

1. Students liked unit-level feedback. They could easily see where they should spend their time to prepare for an exam.
2. Students liked click recommendations. It was easy to click on a concept they were struggling with to receive practice problems or videos to help remediate their lack of mastery.

Phase 2. Based on this feedback, we redesigned our content recommender and now present version two. The changes made in version two (see Figure 4) specifically addressed the challenges that we discovered in version one of our content recommender. In this prototype, the design is simpler because we removed the concept lists at the top and removed the advanced toolbar. Also, it is easier to see the concept names because they are overlaid on top of the bar that indicates the mastery score. Another feature that made this design more user-friendly is having the "Send Feedback" button at the top right of the screen instead of below in the dashboard.

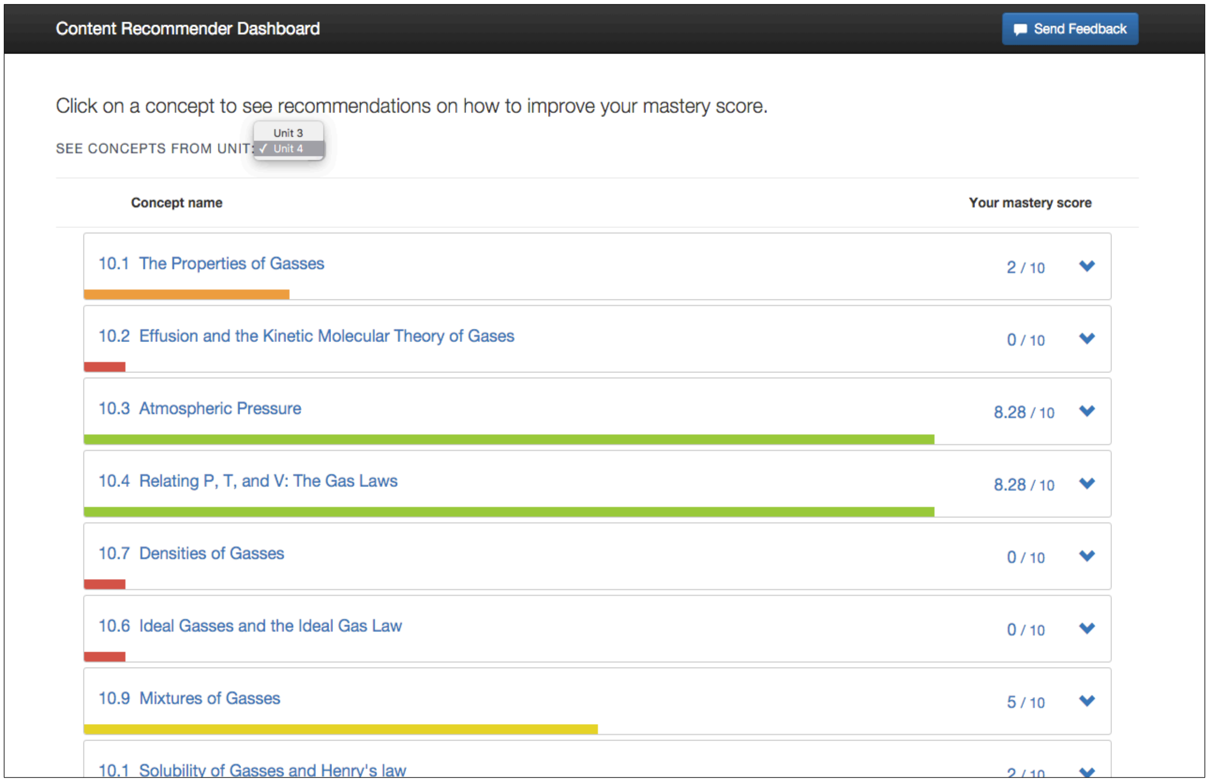

Figure 4. The unit view of the content recommender version two.

The final change on the mastery score page was the addition of an accordion dropdown for recommendations instead of taking users to a new page (see Figure 5). This allowed users to easily see where they were struggling and see recommendations to improve on the same page.

We again solicited informal feedback from students and instructors (N=10). The evaluation was focused on whether students would use the system, how easy the system was to use, and how students would act as a result of the information provided in the dashboard. Based on this, we determined our design still had a few weaknesses: (1) with an accordion dropdown you have to scroll within the recommendations tab and scroll down to see all of the concepts (scrolling within a scrolling page is difficult to navigate), (2) users cannot see video usage in relation to assessment data, and (3) the drop-down recommendations bar was a little too cluttered. These weaknesses will be addressed in the third version of our content recommender. We also discovered similar strengths to the previous dashboard prototype: students and faculty liked that it was easy to see which concepts a student was struggling on and that it was easy to click on a concept to get recommendations. Students also liked that they could see their mastery score as a number in addition to the sliding colored bar.

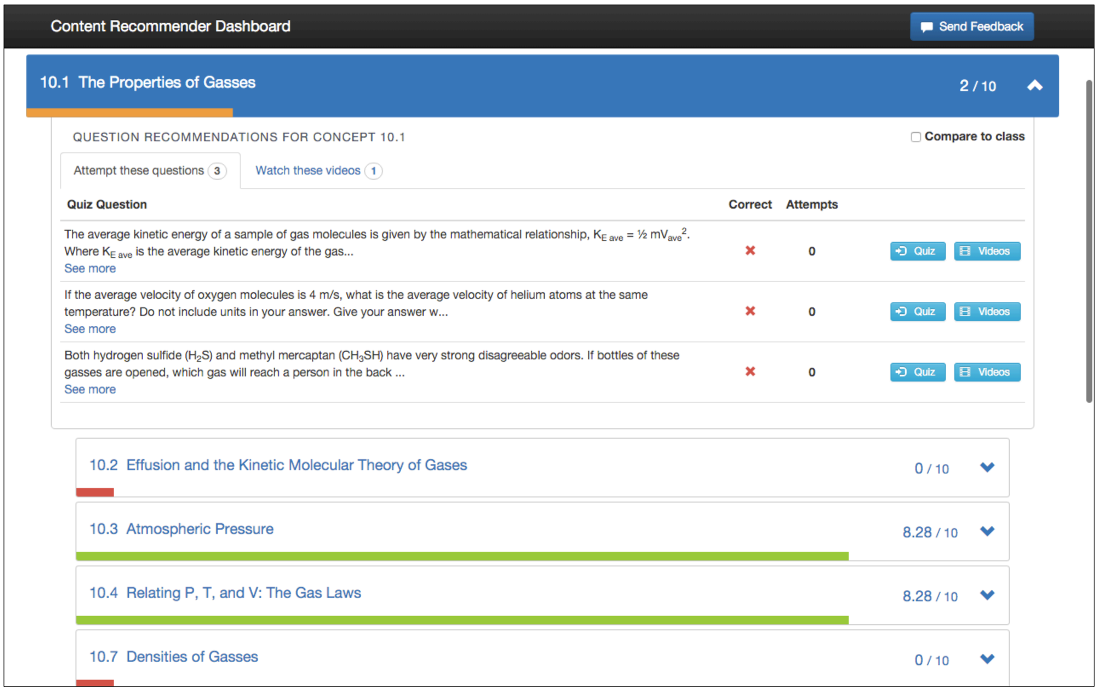

Figure 5. The individual recommendation view of the content recommender version two.

Phase 3. The final version of the content recommender we will discuss here is the scatterplot content recommender (see Figure 6). This prototype was designed to address the challenges discussed with the previous prototypes and augment the affordances of the design discovered from user testing. First, we created a scatterplot visualization of mastery score and video use so a user could easily track video use and mastery score across concepts at a glance. We then put the recommendations table next to it (activated by clicking a point or concept in the scatterplot) so the user could see an overall view of their knowledge *and* recommendations at the same time. This side-by-side presentation eliminated the scrolling within a scrolling page problem with version two. Beyond addressing the challenges from previous prototypes, we also included a total mastery over time line chart so users can see how they are progressing through the course over time (see Figure 7). By providing students with views over time, students can reflect over their behaviors in the course, become more aware of the way in which they learn, and change their learning behaviors to match with their goal for the outcome in the course (Shute, 2008; Hacker, Dunlosky, & Graesser, 1998).

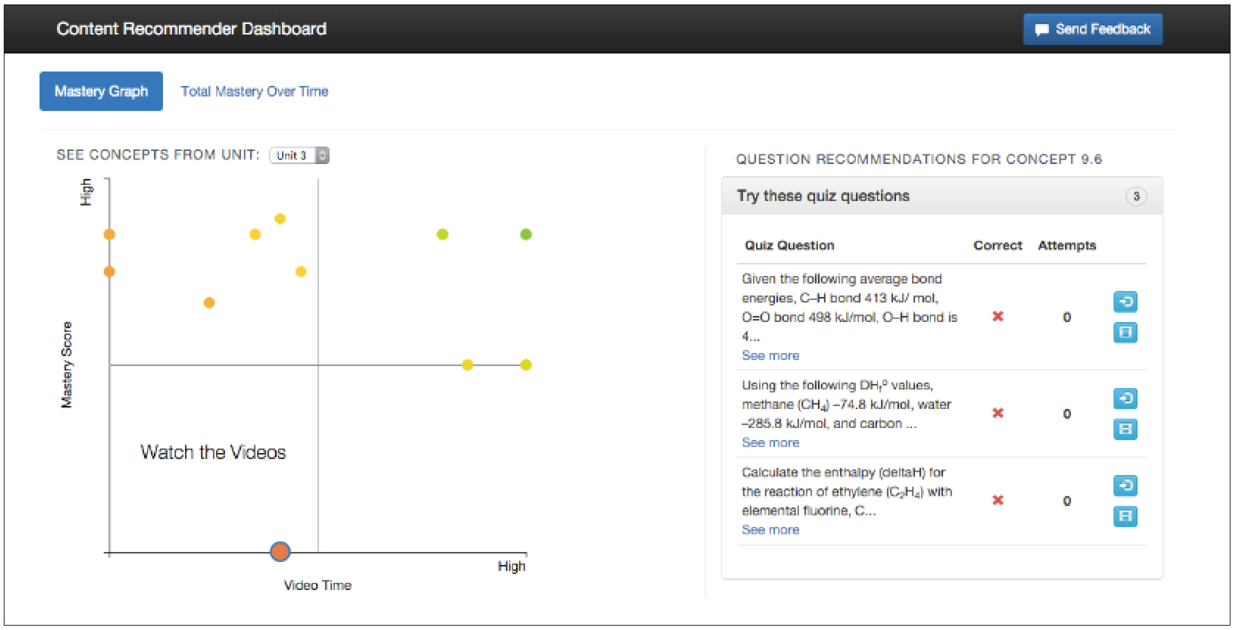

Figure 6. The scatterplot view of the content recommender version three.

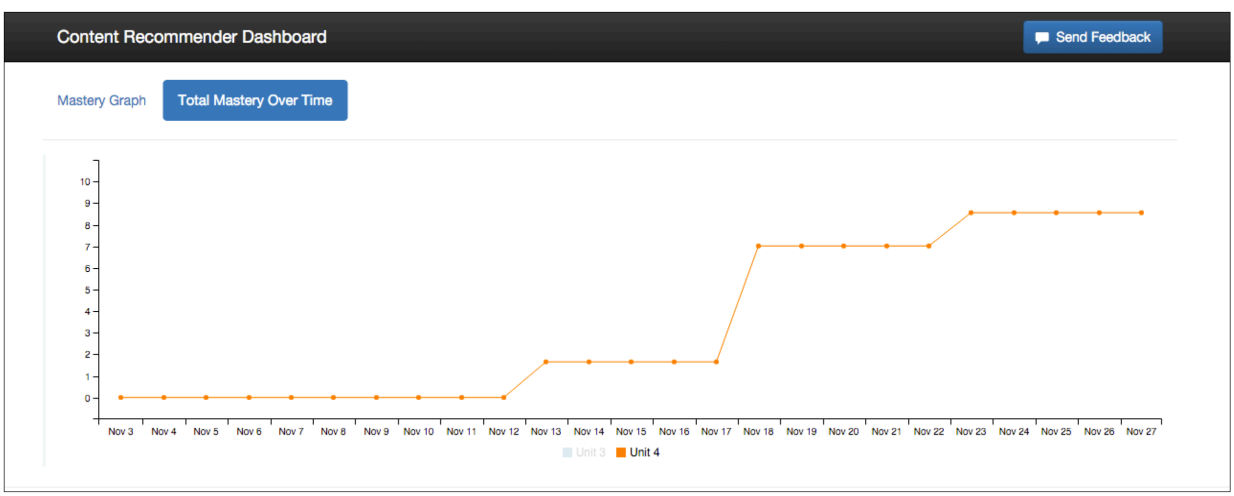

Figure 7. Total mastery over time view for the content recommender dashboard.

We again solicited informal student and faculty feedback (N=10). Faculty and students liked the progress over time chart and liked that students could see their video-watching use compared with their assessment data. Students said they would not use the dashboard every day, but they could see themselves using it once a week to self-assess their study habits in the course. Based on this positive feedback, we were finally ready to implement the dashboard in an actual class and get additional feedback from students in focus groups and from a survey. Before we report on this data, we first discuss the design and development of our skills recommender dashboard.

Student Skills Recommender

The skills recommender was designed to help students improve their metacognitive strategies, such as time management, persistence, knowledge awareness, online activity, deep learning, and consistency (Kerly, Ellis, & Bull, 2008; Muldner et al., 2015). Each of these skills was calculated using the online student interactions within quizzes and videos in the course. We began with simple measures that can be expanded on in future research. These skills were chosen to be represented in the skills recommender because they were either theoretically predictive of student success, as found in the literature, or were predictive of student achievement in our exploratory analysis. We calculated each skill using the following formulas:

1. *Time management* is a measure of planning ahead. It is calculated by taking the number of online interactions that occur between 11:00PM and 5:00AM and dividing by the total number of online interactions. This feature was included because in an exploratory analysis we discovered it was predictive of student success even in the presence of other variables.

2. *Persistence* is a measure of how long students will try to solve a problem or watch a video before giving up. It is calculated using the total number of quiz question attempts and videos watched, both normalized based on the class average. Persistence was included because it has been found to be a predictor of student success (Lent, Brown, & Larkin, 1984).
3. *Knowledge awareness* is a measure of how accurately students can rate their confidence on the quiz questions. If a student answers a question correctly with high confidence, their knowledge awareness score increases; if they answer a question incorrectly with high confidence, their knowledge awareness score decreases. This variable was included because in our exploratory analysis we found that it was a predictor of student success.
4. *Online activity* is an approximation of time-on-task. It is the total amount of time a student spends online, normalized by the class average. This variable was included because time-on-task is correlated with student achievement (Stallings, 1980).
5. *Deep learning* is our word choice for the opposite of gaming the system. Gaming the system is when a student tries to manipulate the learning software in order to finish the assignment as quickly as possible. We can detect gaming the system when users have multiple attempts within a short time period, repeatedly click "show answer" on every question, or click on a hint immediately after loading a problem. Not gaming the system has been found to be a good predictor of student achievement, so we included this variable in our system (Baker, Corbett, Koedinger, & Wagner, 2004).

6. *Consistency* is a measure of how frequently a student works on online homework. It is calculated by taking the number of days they have online activity for the class and dividing by the total number of days within the time frame specified. Consistency was included because it is inversely proportional to procrastination, which has been shown to negatively impact student achievement (Steel, 2007).

These student skills are not perfectly defined nor named, but still provided a reasonable starting point to understand whether a skills dashboard can be beneficial to students. Definitions of each skill along with an explanation of how they were calculated were provided in the dashboard to be transparent to students.

Phase 1. We decided to parallel the structure of our content recommender version one by including a feedback toolbar on the right-hand side, an advanced toolbar in the upper right, and a quick overview of the strongest and weakest skill on the main page (see Figure 8). Then, we provided students with a skills graph (a radar chart) that gave them a quick overview of all of their skills at the same time (see Figure 9).

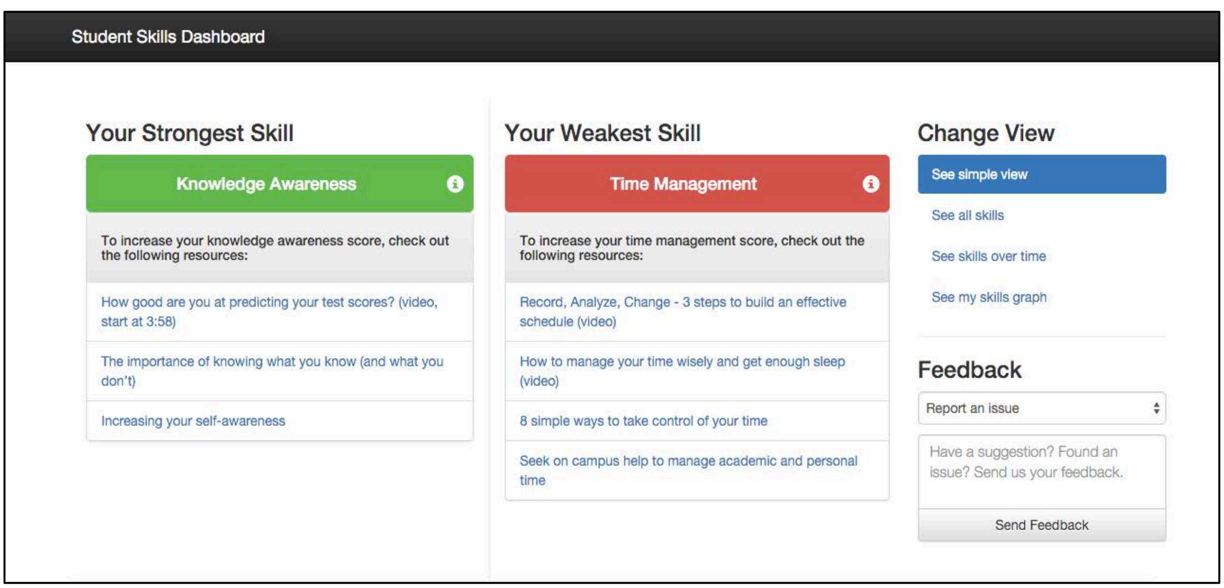

Figure 8. The simple view of the student skills recommender version one.

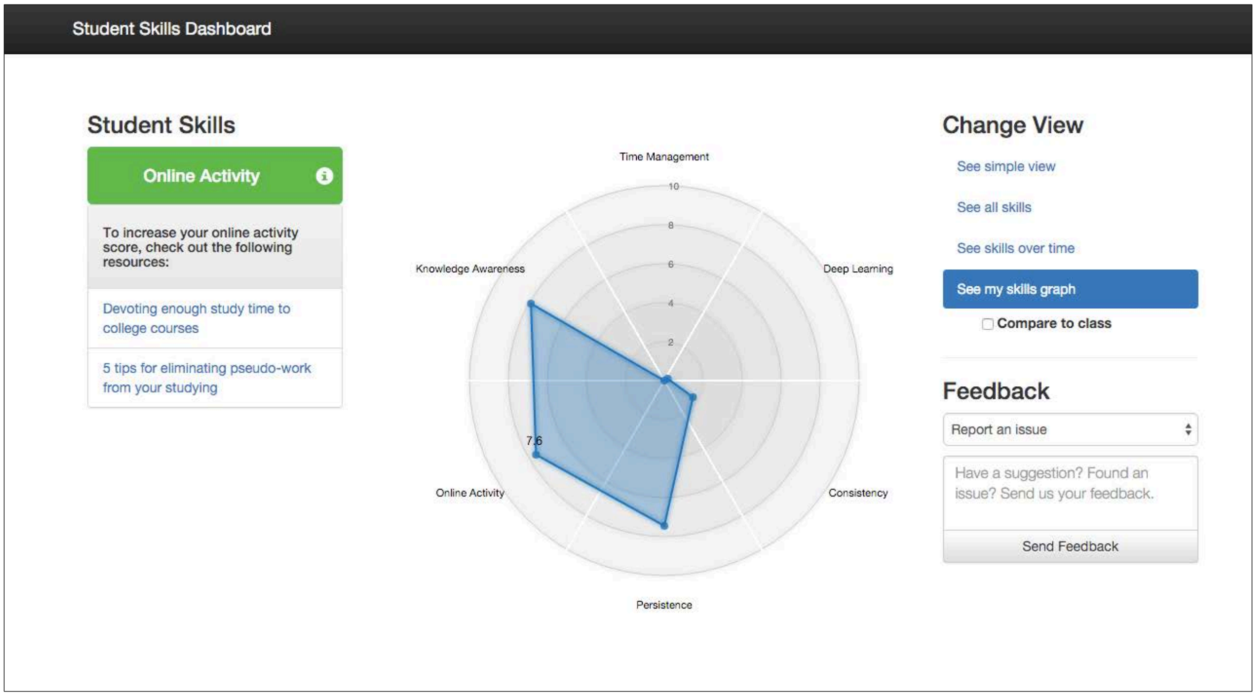

Figure 9. The skills graph view of the student skills recommender version one.

We solicited informal feedback from faculty and students (N=10) on our design and were able to identify a few changes that needed to be made. Students and faculty liked the radar chart, as it was the most intuitive way of seeing an overview of all skills at the same time (Few, 2006), but it was not seen as often because it was buried within the advanced toolbar settings. In addition, the radar chart, feedback tool, advanced toolbar, and skill suggestions box on the page made everything too cluttered and hard to use. These suggestions were easy to fix and resulted in the skills recommender version two.

Phase 2. The skills recommender version two, the final version we will present in this paper, had the radar chart overview of all the skills on the front page as soon as the dashboard was loaded (see Figure 10). Then, students could click on a point or skill on the graph to receive recommendations right next to it on the right side of the page. We also moved the advanced toolbar from the upper-right side of the page to the left side of the page to make it more like a regular navigation bar. Similar to the content recommender, we moved the feedback bar up into the header for a cleaner look for our dashboard. One new feature that we added to the skills recommender is the skills over time line graph (see Figure 11).

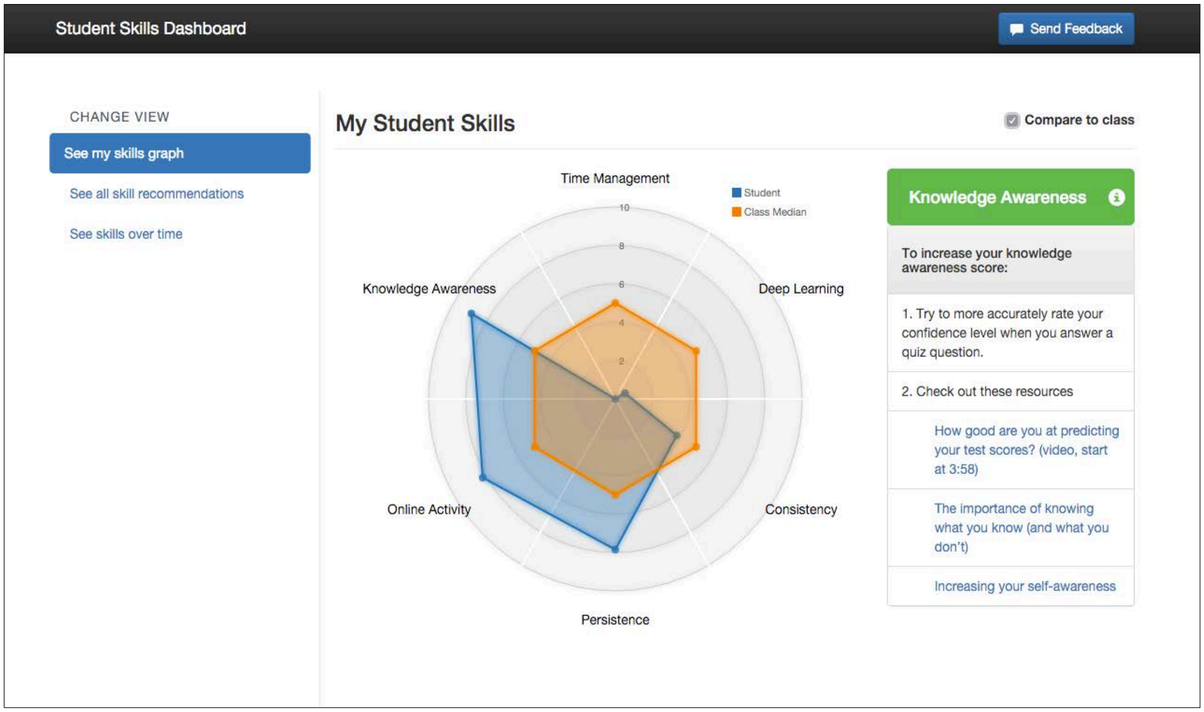

Figure 10. The skills graph view of the student skills recommender version two.

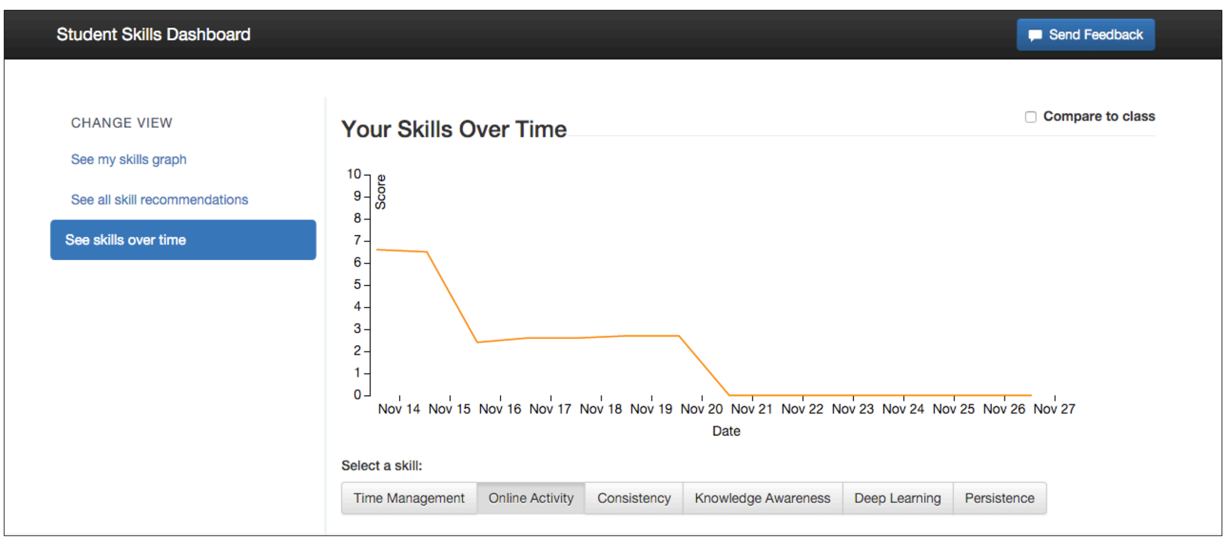

Figure 11. The skills over time view for the student skills dashboard version two.

We hypothesized that this would help students reflect on their learning as they see increases and decreases in various skills over time. Students mentioned they would use this dashboard once or twice per week to see how their skills were changing over time, then they could change their behavior based on the feedback received from the dashboard. Test users easily figured out how to use the dashboard, so we decided we were ready to implement the dashboard in an actual class.

Methods

The participants in this study (N=180) were selected from an introductory blended chemistry course at a large private United States university. Students met three times per week for lecture and two times per week with a teaching assistant to go over extra practice problems. Students were instructed to watch videos online, take quizzes online, and complete homework online. The quizzes were required and the videos were optional for all students regardless of their involvement in the research study.

Focus group times were determined by sending out a survey with possible times, with instructions for the student to list when they were available. Students were grouped based on their availability into groups of five or six. We conducted four focus groups which were held for sixty minutes. The audio was recorded, transcribed, and coded using an open coding protocol in order to find trends and common themes across student responses.

A dashboard feature perceptions survey was given to students at the end of the semester. The survey was sent to all consenting students; we received 70 responses (39% response rate). The survey questions used were adapted from existing dashboard surveys and focused on student perceptions of system usability and usefulness (Verbert et al., 2013; Verbert et al., 2014; Yoo, Lee, Jo, Park, 2015). The focus groups and survey were conducted to primarily understand the learning analytics needs of students within the context of an LAD.

Results and Discussion

We will report on the focus group findings and our results from the dashboard perceptions survey. The discussion will happen for each analysis (e.g., focus groups, survey) in this section instead of in a separate discussion section.

Focus Group Results and Discussion

Focus groups were conducted to understand student perceptions on the usability and utility of the features in our dashboards. In addition, toward the end of the focus groups, we used a think-aloud protocol to understand how students understood and interacted with our dashboards. Focus groups were audio recorded, transcribed, and coded using an open coding protocol allowing the coders to include additional codes if necessary throughout the coding process. The student learning analytics needs that emerged from the focus groups are summarized in Table 2.

Table 2.

A Summary of Focus Group Themes

Category	Number of statements
Useful features	39
Requested features	32
Course content	28
Bad features	17
Frequency of use	15
Course synchronization	11
Comparison between dashboards	7

First, we will discuss features students liked and found useful. Second, we report on features students would like us to change. Third, we review the new features students want to be included in future iterations of the dashboard. Finally, we briefly summarize each of the categories with only a few student statements.

Useful features. We identified five subcategories within the useful features statements that described the reasons students liked certain features of the dashboards for pedagogical reasons: knowledge awareness, recommendations, reflection, usefulness, and motivation. Of the 39 good feature statements, seven of them address *knowledge awareness*. Students said they liked the content recommender because it improved their knowledge awareness. One student said, “[it] helps us to know what we should study for tests.” Another student said, “I don’t always remember which questions I struggled on so [I] have to go back through . . . but it’s nice that it just tells you.” This shows that one necessary goal of an LAD should be to help students become more aware of their knowledge gaps.

There were seven statements regarding the importance of *recommendations*. One student mentioned, “I can look at what the questions were and if I wanted to go back and review it, it’s right there.” Another said, “I think that is useful, it tells you . . . what section it is in the book so you can look it up.” These comments indicate that including recommendations within a dashboard is a convenient way to help students act on the knowledge gaps or skill gaps they identify while using the dashboard.

There were six statements out of the total 39 about *reflection*. Students liked that they could see their mastery scores or skill scores over time because it helped them reflect on their learning. One student said, “I’m trying really hard at the quizzes but I’m just not getting it right. But then [the dashboard] will say ‘persistence, just try a couple more times before you click show-answer’ and you’ll realize, ‘Oh, maybe I’m clicking show-answer a lot.’” This shows that supporting student reflection is an important role in an LAD and it can help students succeed in online learning.

The final two categories, *usefulness* and *motivation*, only had a few comments (N=6). These statements addressed that the dashboard in general was both useful and motivating to students. Some of the students mentioned the dashboards were like a game. They would return frequently to look at their graph to see if it had changed from the last time they looked.

Bad features. We identified four subcategories within the bad features statements: confusing, not user-friendly, not personalized, and inaccurate data. Out of the 17 bad features statements, eight of them were comments from students who were *confused* with something in the dashboard. Students were confused about the purpose of rating their confidence, the class median, the skills radar chart, the compare to class metrics, the concept numbering, and the definition of skill scores. The majority of these features are in the skills recommender dashboard and will serve as evaluation points for future iterations of our dashboards.

There were only three statements indicating the dashboards were *not user-friendly*. One student said, “I entered into the dashboard . . . but I wasn’t really sure what to do with it.” Another student was able to figure out the dashboard, but stated, “When you scroll over the main body of all the points it gets dark, and I feel like it should do something . . . but it doesn’t do anything.” This shows great care should be taken to ensure a dashboard is intuitive and easy to use for all students. It also could mean students should be trained at the beginning of the semester so they can use it effectively throughout the semester.

Four student statements indicated the dashboard was not useful to them because of a *lack of personalization*. One student explained his frustration about article recommendations this way, “I just feel like it’s a lot and I don’t know if I would have time to just go through and read articles." Another said, "That's not very personalized . . . and so instead it feels like being bombed with information." Yet another mentioned, "If I click on Time Management and every single time this is all that's there, then over time I'm not going to look at it anymore." This shows the importance of a personalized and streamlined experience for the student. If they cannot find needed information quickly without being overloaded with too much information, the dashboard will not be useful for them.

The final two statements were concerned with *data inaccuracies*. One student said, "Why does it always say that I have two attempts? Because I'm pretty sure I didn't put two attempts on every quiz." This shows that it is important that students trust the dashboard enough to believe the data visualizations and recommendations. If they think the data is inaccurate, the dashboard is not a useful support tool for them.

Requested features. The requested features statements analysis resulted in four subcategories: additional resources, centralized location, teaching assistant dashboard, and comparison to class. There were five statements from the original 32 in this category that addressed the need for *additional resources*. Students wanted more content resources, such as YouTube videos or content links, and more practice problems related to questions they struggled with.

There were 13 statements concerned with the dashboard being a *centralized location* of student online work. If they have to take a quiz in one application, then look at their grades in another one, and finally go back to view content in yet another one, it makes the online experience more difficult to navigate. One student stated the ideal in this way, "Click on the dashboard, that's where all your quizzes are, that's where you take them, you see what you haven't taken, you see how you did." These statements show the importance of a dashboard having as much online student interaction data as possible so students can have a seamless and integrated online experience.

Six statements out of the original 37 wanted enhanced *compare to class* functionality. Students indicated they wanted to be able to compare their quiz grades and resource use with the "A" students in the class. One student described their reasoning like this: "I feel like if you can see everyone else is getting better grades than I am and they're all using the videos and I'm not, well that's probably why . . . I feel like that would help me." Another student said, "I think [comparing to the class is] important because then you could . . . say OK I really am getting chemistry, it's just no one is getting this one part." While comparing grades with students may motivate or demotivate depending on whether the student falls above or below the class average, these students would be benefitted with improved compare to class functionality.

The final category students mentioned (N=2) for feature improvement is a *teaching assistant dashboard*. This dashboard would allow a teaching assistant to easily determine what concepts students are struggling with so they could spend more time on it during review sessions.

Additional comments. Regarding how frequently the students would use the dashboards, most agreed they would not check it every day. Students reported they would use the content recommender right before an exam or if they felt like they were struggling or falling behind. They also mentioned they would periodically check the skills recommender to see how their skills were changing over time.

The course synchronization statements indicated that the dashboard would be more useful to students if a bigger portion of their online work was included. Students had to complete an online quiz within the analytics system but also had to complete online homework outside of the analytics system. This made the dashboard less relevant because it only had half of the course data instead of all of it. A dashboard is only as good as the data going into it.

Dashboard Perceptions Survey Results

The purpose of the dashboard perceptions survey was to better understand student access to the dashboard, student use of the dashboards, and student perceptions of the dashboards. The survey was sent to 130 students and 70 responses were received.

Despite sending emails to the students' personal emails notifying them that they had dashboard access, posting an announcement to the learning management system, providing an accessible link in the learning management system, and presenting the dashboards to students in class, 29% (N=18) stated that they did not know they had access to a dashboard. This could be one reason students did not use the dashboards as much as we expected—they did not even know they had access to it.

The next question, only given to students that were aware they had access to the dashboard, asked how much students used the content and skill recommender dashboards. The content recommender was used at least two to three times per month by 29% of the students (N=18). We thought most students would use the dashboard at least two to three times per month, but only 29% of students used the dashboard that frequently. The skills recommender was used by even fewer students, with only 11% of students (N=7) using the dashboard at least two to three times per month.

To follow up on students with low dashboard use, we asked why they did not use the dashboards. Students indicated three reasons why they did not use the dashboards: (1) they did not feel it was necessary—they did well without it, (2) they did not know if it would be helpful and were confused on how it would help them in the course, and (3) there was so much other work to do in the course they did not have time for the dashboard. The purpose of our dashboard was to help students save time as they prepared for exams, so, for future research, a student dashboard training could be held at the beginning of the semester to show students how to use it, why it is beneficial, and how it would save them time. This could potentially increase student use of the dashboards.

For students that used the dashboards, we asked them to rate the content and skills recommender dashboards in four categories: user-friendly, interesting/engaging, useful, and informative. For the content recommender dashboard, we found that 79% of students responded with somewhat agree, agree, or strongly agree to all four categories. This shows that the majority of the students that used our dashboards found them user-friendly, engaging, useful, and informative (see Figure 12).

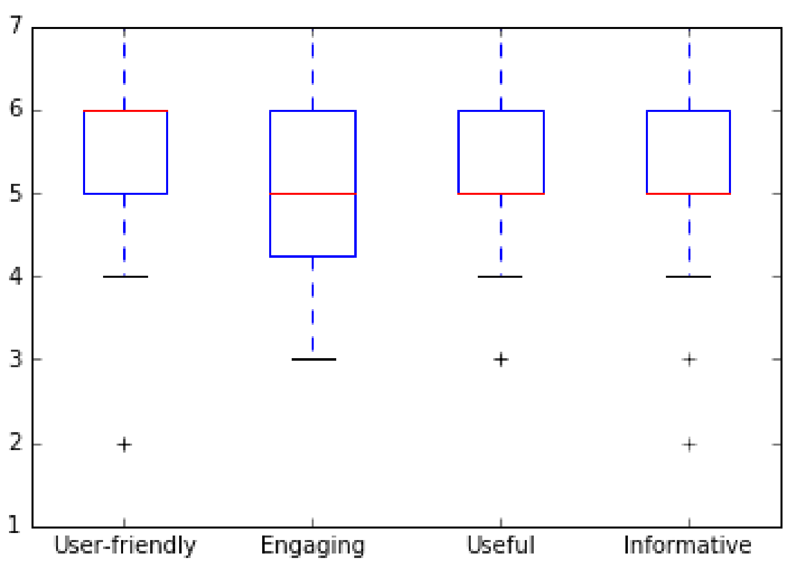

Figure 12. Boxplot indicating mean, quartiles, and outliers for content recommender survey. Note: neither agree nor disagree (4), somewhat agree (5), agree (6), and strongly agree (7).

For the skill recommender dashboard, we found that 85% of students responded with somewhat agree, agree, or strongly agree to all four categories. Even though student use was lower with the skill recommender dashboard, students that used it found it user-friendly, engaging, useful, and informative (see Figure 13).

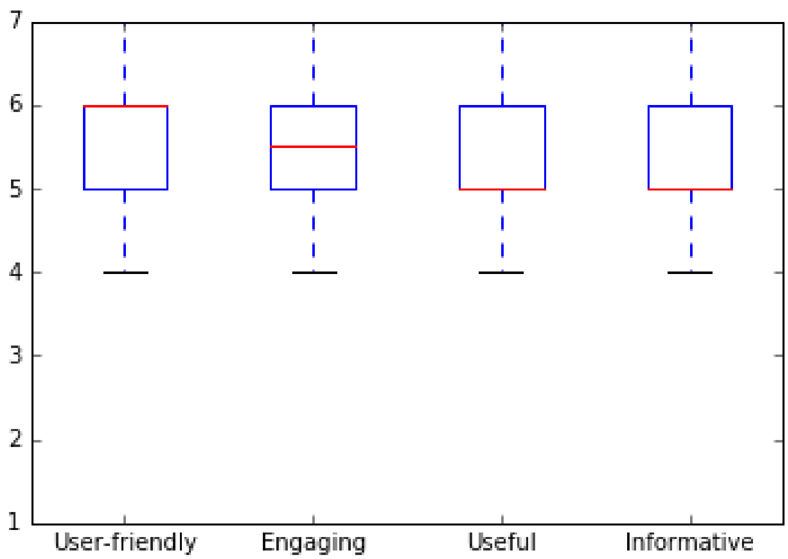

Figure 13. Boxplot indicating mean, quartiles, and outliers for skills recommender survey. Note: neither agree nor disagree (4), somewhat agree (5), agree (6), and strongly agree (7).

Limitations

While this study provided detailed descriptions of dashboard design, no experiments were conducted to determine the effectiveness of these systems. Future research should empirically examine these dashboard systems to determine if the dashboard systems have any impact on student behavior, student achievement, or student skills.

The feature review conducted after the design and development of the dashboards mainly examined dashboard features, not student perceptions or emotions. Future work should examine how learning dashboard systems can affect student emotion, as well as better investigate student perceptions of these systems.

Despite regularly obtaining feedback on our designs from faculty and students, students still did not use the dashboards as much as we believed. This could illustrate a potential flaw in our feedback process, as students may not know what they like and dislike until they are actually using it in a course. In future dashboard studies, conducting pilots in real classrooms could be more informative to better understand student perceptions.

Research Implications and Future Research

The results from this study show the need to not only properly design, prototype, and test with feedback from students and instructors, but to also consider implementation fidelity and adoption. In our testing, students enjoyed the dashboard system and felt like it was a helpful tool, however students did not use it very much. We believe this could be because it was not implemented properly in the course. A needed follow-up study to this work is a design-based research study investigating how to increase student use of learning dashboard systems through course structure changes, instructor practice changes, and dashboard design changes.

Most articles on dashboards do not report on student use of LADs, but this is an important metric in evaluating LADs and determining their effectiveness (Bodily & Verbert, 2017b). Conducting an experiment on the efficacy of LADs without analyzing how students are using the LADs is not as effective because student use could be the reason for no treatment effect and could invalidate actual treatment effects (i.e. if no one used it but there was an effect, the effect was not because of the dashboard). Because of this, researchers should report on how students use LADs to inform their experiments.

In addition to evaluating dashboard interface issues, future research should examine the quality of resource recommendations and dashboard content to understand what students want in a dashboard, how students respond to certain content in a dashboard, and why students are motivated to use certain dashboard features.

In our study, only 25% of students used the dashboard multiple times throughout the semester, but there were more than 25% of students who did not have an “A” in the class. LADs should support students and provide feedback in a way that supports student motivation and engages students. We are already making classroom and dashboard design changes to foster increased use of our LAD. Future research should examine how to motivate students to engage in LAD feedback.

Another future research area is to examine the effect of these dashboards on student behavior and student achievement. Verbert et al. (2014) and Schwendimann et al. (2017) reported that only a small percentage of articles on learning dashboards have reported on experimental results when using appropriate methods. Experimental methods such as randomized control trials or quasi-experimental methods should be used to evaluate the effectiveness of these systems. One of the next steps in our research is to conduct a randomized control trial to see what effect the dashboards have on student behavior and achievement. Another interesting future research area would be to investigate the similarities and differences in implementing these dashboards in different academic disciplines.

Conclusion

Learning analytics dashboards (LADs) provide real-time feedback, recommendations, and/or visualizations to students in order to support student reflection and knowledge awareness in online environments. We have designed and developed two real-time student dashboards: a content recommender to help students identify their knowledge gaps and a skills recommender to help students develop metacognitive skills. We used a practice-centered iterative design process for rapid prototyping in our development process and implemented interoperability standards (LTI and xAPI) to have a more modular and scalable system. To understand student needs within the context of our dashboards, we conducted focus groups and administered a student perceptions survey. The focus group data helped us determine what features of our dashboard should be improved or removed in future iterations. The perceptions survey helped us understand student perceptions of our dashboard; the majority of students found our dashboards user-friendly, engaging, informative, and useful. Students requested additional features such as adding more resources to the dashboard, making the dashboard a centralized location, providing a view for a teaching assistant or instructor, and centralizing a compare to class functionality.

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ARTICLE 3

Increasing Student Use of a Chemistry Learner Dashboard Using a Design-Based Research Approach

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Abstract

In this paper we examined which core attributes (dashboard design changes, instructor practices, and course structure changes) affect student use of a chemistry learner dashboard. We used a design-based research approach across three semesters of dashboard implementation. Our dashboard displayed unit-level feedback collected from students as they interacted with online quizzes and high-quality videos. We implemented two dashboard evaluation surveys, one in the first iteration, and one in the third iteration, and tracked student dashboard use across all three semesters. Based on the research findings across the three iterations of our study, we found that increasing student trust in and helping instructors adopt learner dashboards can increase student use of the dashboard. Specifically, the following techniques may be helpful in increasing student dashboard use: providing dashboard training for students throughout the semester, increasing the quality of data displayed in a dashboard, and improving dashboard usability so students perceive it as being more useful. Our findings support self-determination theory, specifically student autonomy and student competence, and we make contributions to learner dashboard adoption theory.

Keywords: online homework system, learning analytics, dashboard, self-determination theory, autonomy, competence, resource use

Increasing Student Use of a Chemistry Learner Dashboard Using a Design-Based Research Approach

Online learning is increasingly commonplace in university chemistry courses (Allen & Seaman, 2015). One of the affordances of online learning systems is they allow students to complete practice problems, progress as quickly as they want with the goal to achieve content mastery (Malik et al., 2014) and receive feedback in real-time. Some examples of these systems include Pearson's Mastering, ALEKS, and Sapling Learning. These systems provide hints, feedback, or personalization at the question level and recommend resources to remediate student knowledge gaps. While helping students at the question level is beneficial, few systems provide personalized feedback at the unit or exam level. It is important to display feedback on concept mastery at the unit level, as this helps students identify knowledge gaps across concepts in a unit to prepare for exams (Nicol & Macfarlane-Dick, 2006).

Learner dashboards are a good example of feedback systems that display concept mastery or student resource use at the unit or course level. Learner dashboards are defined as "a single display that aggregates multiple visualizations of different indicators about learner(s), learning process(es), and/or learning context(s)" (Schwendimann et al., 2017). While a lot of research has been done on learner dashboards (Bodily & Verbert, 2017a; Verbert et al., 2014), only a few learner dashboard studies actually tracked and reported student use of the dashboard (e.g., Kuosa et al., 2016; Santos, Verbert, Govaerts, & Duval, 2013; Hatziapostolou & Paraskakis, 2010). Furthermore, these studies found that many students did not take full advantage of the dashboard. Student use of learner dashboards is important to increase the rigor of learner dashboard research, provide an explanation for empirical results, and understand how students use dashboard tools.

To address this gap, we have developed a learner dashboard with functionality to track students as they interact with the dashboard. Our learner dashboard tracks student mastery of each topic throughout a unit. Then, it provides students with a summary of their mastery to help them identify knowledge gaps. Students can click on a concept they are struggling with to view resources associated with that concept in order to remediate their lack of knowledge. Students can use this tool as a form of exam preparation to master content material and increase their score on an upcoming exam. Another unique feature of the dashboard is that it enables student autonomy in allowing students to choose what, when, and how often they would like to study. One potential problem with enabling student autonomy is students often do not complete activities when they are optional (Grabe & Christopherson, 2008). In this paper we use design-based research (Barab & Squire, 2004; Wang & Hannafin, 2005) to investigate how to increase student use of our optional learner dashboard through class structure, instructor practice, and dashboard design changes.

Literature Review

We examine three distinct bodies of literature: existing Online Learning Systems (OLSs), student-facing learning analytics dashboards, and student use of learning feedback systems.

Existing OLSs

While many OLSs simply digitize practice problems from the textbook to an online platform, some use more advanced responsive and responsive-adaptive techniques. Responsive OLSs, such as Pearson's Mastering Chemistry, give hints and feedback but do not change the order or content of an assignment based on student answers. Responsive-adaptive OLSs, such as Aleks, recognize areas where a student lacks mastery and tailor their learning according to those weaknesses by providing additional practice and resources. The pace, content, and order of the assignment is unique to the individual (Eichler & Peeples, 2013). Students who used a responsive-adaptive OLS spent more time working problems, and performed significantly better than students who used a responsive OLS (Eichler & Peeples, 2013). Responsive and responsive-adaptive systems personalize learning at the question level and require students to complete activities to increase mastery. Making these activities required for course credit increases the number of students that complete them (Parker & Loudon, 2013), however, it decreases student autonomy and affects student attitudes toward assignments (Black & Deci, 2000). We are interested in examining the factors that increase student use of a unit-level learner dashboard, an optional system that should promote student autonomy.

Student-Facing Learning Analytics Dashboards

A learning analytics dashboard is a visualization of student activity data collected as students interact with online resources (Schwendimann et al., 2017). These dashboards are intended to provide stakeholders with information that can be understood at a glance (Few, 2006). There have been a number of previous literature reviews done in this area (Verbert et al., 2013; Verbert et al., 2014; Schwendimann et al., 2017; Bodily & Verbert, 2017a). However, these reviews have not addressed the ways in which students use learning analytics dashboards or how we can increase student use of these feedback tools. Research on student use has implications for previous studies because experimental results may be biased if researchers do not take into account how students use the system. Student use may explain why a dashboard has no effect on student achievement, but it would not be identified as a confounding factor if the student use data was not being tracked. In this paper, we address the issue of how often students use a student-facing learning analytics dashboard and how course structure, teacher practices, and dashboard design changes can increase student use.

Student Use of Learning Feedback Systems

We have categorized articles that report data about student use of reporting systems into three categories: insufficient reporting, low student use, and potential evidence for increasing student use.

Insufficient reporting. Kuosa et al. (2016) used Mixpanel to track how students were using the visualization tool TUT LA that they developed. Student dashboard use metrics were not provided in their article, but they mentioned the interactive visualization was used by the students more than any other visualization type in the study. This student dashboard use reporting is not helpful in understanding student use of optional feedback tools and does not increase the understanding of how to increase student use of optional dashboard tools.

Santos, Verbert, Govaerts, and Duval (2013) created a dashboard that was implemented with 56 students in three different courses. They reported on dashboard use across the three semesters in the form of a Google Analytics activity chart, but do not break down student use of the dashboard by course or student. They also reported that the dashboard was visited a total of 840 times over the course of one month. These metrics are interesting within the context of this study, but do not inform future research regarding what dashboard design elements or course structure changes influence student use of dashboard systems.

Ott, Robins, Haden, and Shephard (2015) created an infographic dashboard to provide 60 students with information on how to succeed. They used self-report methods to track dashboard use and found that 94% of the students referred back to the dashboard at least once during the semester. They also found that 80% of the students used performance indicators in the dashboard throughout the semester. These descriptive statistics are useful in understanding how students used the dashboard during that semester, but do not provide generalizable information on how to increase student use of optional dashboard tools.

Low student use. Santos, Boticario, and Perez-Marin (2014) described building and implementing an educational recommender system. Out of 182 participants in their study, 348 recommendations were followed in the first half of the course and 166 recommendations were followed in the second module. This means each student, on average, followed three recommendations throughout the course. Following three recommendations on average throughout the entire course means many students are not using or taking advantage of the recommender system. No suggestions were provided to increase student engagement with these recommendations.

Hatziapostolou and Paraskakis (2010) developed an online feedback dashboard for students and tracked student use of the system. They found that all students accessed the dashboard at least once, but no information was provided to help understand how that access rate was achieved. They also found that 35% of students revisited the dashboard tool before final exams. No suggestions were made regarding how to increase the number of students that revisit the dashboard.

Grann and Bushway (2014) created a competency map dashboard for students. They found that 31% of students accessed the dashboard at least once, about 16% viewed the dashboard repeatedly, and only a few viewed it more than 10 times throughout the course. Many students access the dashboard at least once, but only a small subset of those users accessed the dashboard over time, and an even smaller subset used the dashboard frequently over time. These results indicate that only a small portion of students are taking full advantage of dashboard resources. If these learning analytics systems and dashboards are time intensive and expensive to create, more research is needed to encourage increased student use of these systems.

Tervakari, Silius, Koro, Paukkeri, and Pirttilä (2014) created a dashboard with a few different visualizations. They found that all students accessed the dashboard at least once, but again, do not provide information as to how that access rate was achieved. Additionally, they reported that only five students actively used the dashboard throughout the semester as most of the students were inactive. No information was provided to inform practitioners or researchers how to increase student activity with optional dashboard tools.

Potential evidence. Xu and Makos (2015) used optional notifications to increase student behavior in online discussions. They found that 80% of students chose to activate the notifications for the course. They also found that the discussion behaviors of students who received notifications for discussion activity were positively affected (e.g., posted more, liked more posts, replied to posts more frequently). This study presents an interesting method for increasing the frequency of online student behaviors. Similarly to previous studies, no information was provided regarding how to increase the number of students that activated notifications or how to increase the number of students that acted on notifications received.

Holanda, et al. (2012) used a recommender engine to increase activity on a blog assignment. Initially, six students (50% of the class) interacted (e.g., commented) with the blog post. After a recommendation was sent out, three more people interacted with the blog post, along with two others that had previously interacted with the post. This study had a small sample size, but still provided some evidence that using recommender systems can increase student online activity. No suggestions were provided on how to increase student response rate to the recommendations.

Muldner et al. (2015) examined how student use of a dashboard changed across various conditions in a three class seventh grade experiment. They manipulated how easy it was to access their dashboard in order to change how many students accessed their dashboard tool. There were four groups of students: (1) no button, meaning the only way to access the dashboard was through a complicated set of steps not told to the students, (2) button, meaning students could access the dashboard by clicking the button, (3) prompt, meaning if students self-reported low excitement or low interest, the system would prompt them to use the dashboard, and (4) force, meaning students were redirected to the dashboard and were forced to look at it. They found that as they increased the discoverability of the dashboard (no-button, button, prompt, force) student use increased. The number of times, on average, that students accessed the dashboard were 1.3, 3.1, 6.0, and 8.8 for the respective conditions no button, button, prompt, and force. This study suggests prompting or forcing students to use a system will increase student use of dashboards in autonomous learning environments. However, they also found that forcing students to engage with the dashboard through prompt or force methods negatively impacted student interest in the course.

Summary. Only a few articles have described feedback systems (e.g., dashboards or recommender systems) that track student use of the system. Some of these studies did not report sufficient student use data, others provided simple descriptive statistics about how many students used the dashboard, and others provided potential evidence for ways to increase student use of online systems. However, none of these systems provided detailed student use data broken down by demographic data, learner characteristic data, or student achievement data, indicating what types of learners are using these systems. Additionally, none of them provided information on what design changes, instructor practice, or class structure changes could be made to increase student use of these optional dashboard or recommender systems. We address this gap by developing a student-facing learning analytics dashboard and, using a design-based research methodology, investigate what dashboard design decisions, instructor practices, or class structure changes result in increased student use of dashboard systems.

Our Dashboard

The dashboard described in this paper is a unique form of responsive-adaptive learning that emphasizes student autonomy and choice (Figure 1).

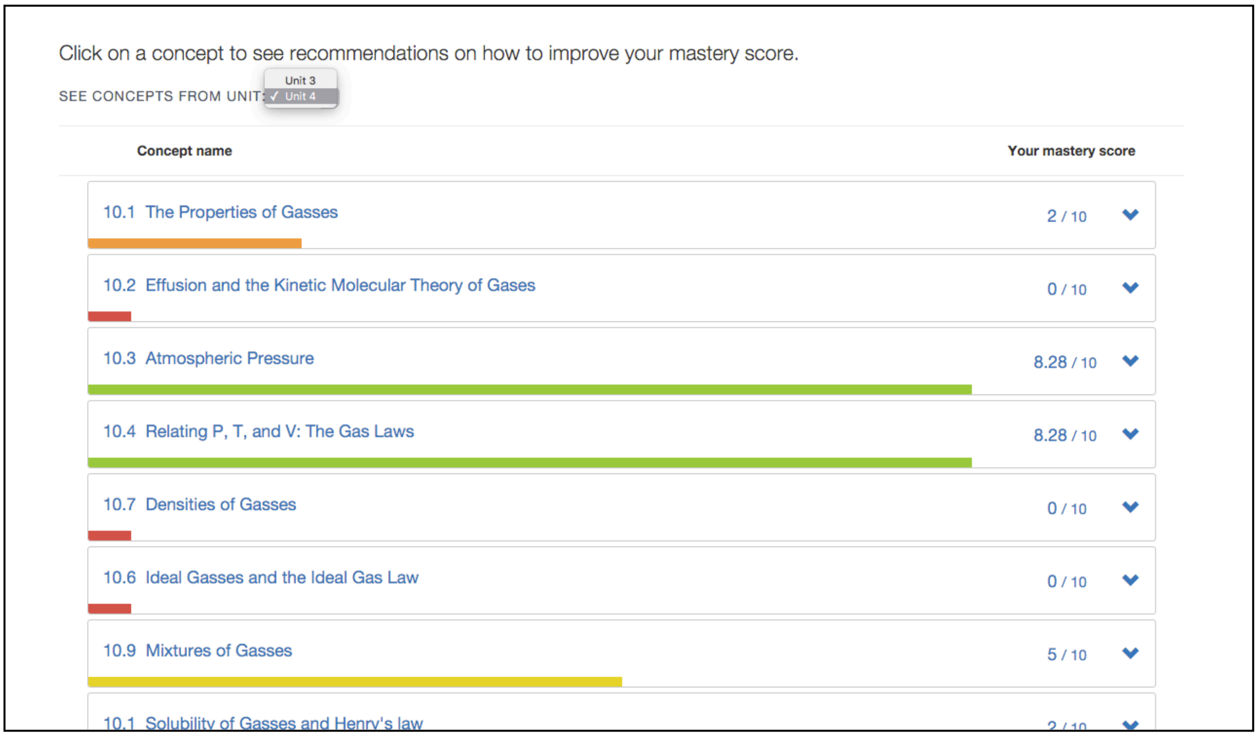

Figure 1. A screenshot of the chemistry dashboard.

Each student takes a responsive diagnostic quiz. The dashboard aggregates the results, combining accuracy and the number of attempts into a mastery score (Bodily, Ikahihifo, Mackley, & Graham, in press, 2018). The dashboard displays the student's mastery score for each course topic and offers links to additional resources such as practice questions, online texts, and videos. Given feedback on their performance, students can choose whether or how to use dashboard resources. The dashboard supports student autonomy, allowing students to decide which topics they want to study and which of a variety of resources to use.

In this paper we seek to address the following research questions:

1. How do changes in dashboard design, instructor practices, and course structure affect student use of an OLS dashboard?
2. What elements of dashboard design, instructor practices, and course structure affect learner dashboard use?

Methods

This study was conducted in an introductory level chemistry course at a large, private, university in the United States. We used design-based research to iteratively design and develop the dashboard for the OLS and to conduct our research.

Design-based research (DBR) is becoming more popular as a research methodology due to its dual focus of improving practice and making theoretical contributions to research (van den Akker, 1999). This approach fit our context of improving student use of dashboard feedback in an autonomous learning environment because we are both (1) trying to understand how to support students in engaging with feedback (research focus) and (2) trying to create a system that will help students succeed in general chemistry (practice focus). Design-based research does not have specific methodologies associated with it, but mixed methods are often used (Anderson & Shattuck, 2012) and have been employed in our DBR approach. In addition, methods and instruments commonly evolve depending on the issues that arise and the questions that need to be answered during each design-based research cycle. This is different from a research experiment that is conducted under controlled circumstances. For example, randomized control trial research designs are used to control for confounding variables by randomizing subjects into treatment and control groups. Each iteration focuses on and tests one specific treatment condition. Conversely, when using a DBR approach, a researcher may change multiple factors each iteration if there is evidence to support the changes. These changes can be easily seen as each iteration is well documented with descriptions of the core attributes pertaining to each iteration. A graphical depiction of this design-based research project can be seen in Figure 2.

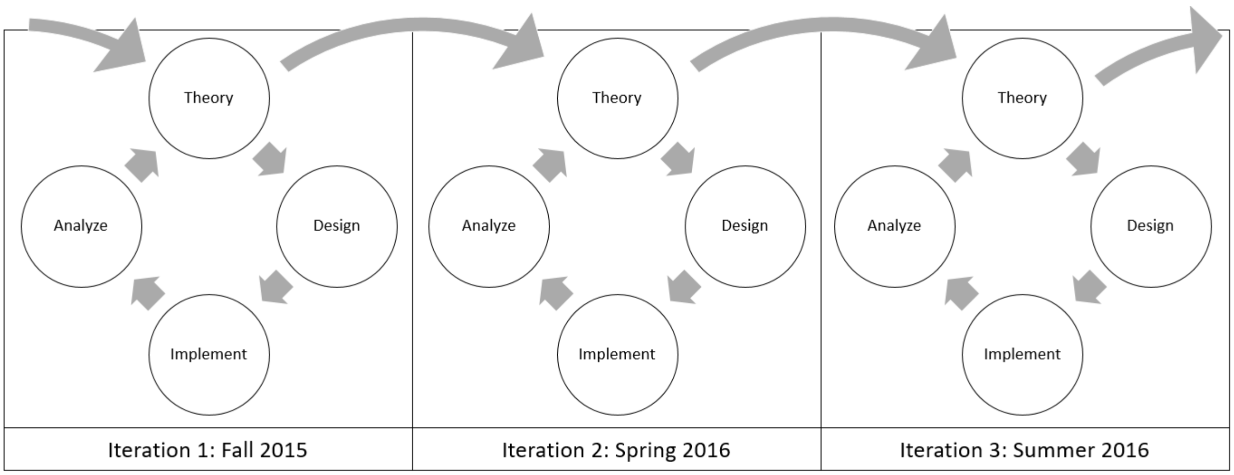

Figure 2. A graphical depiction showing the cyclical process of design, implementation, analysis, and theoretical contributions of design-based research.

DBR methodology is cyclical in nature. Researchers conduct a study and the results of that experiment inform the next study (or iteration). This iterative process continues, with researchers asking new questions as they arise and using data to answer them. Our research findings may look different when compared with other research paper results as we compare and contrast the results from three different studies.

Our design-based research approach included implementations of our dashboard system across three different semesters: Fall 2015 (semester 1), Spring 2016 (semester 2), and Summer 2016 (semester 3). Each semester had unique core attributes that described the dashboard implementation for that semester. We tested whether the core attributes had any effect on student use of the dashboard, our outcome variable, as measured by the amount of clicks students made within the dashboard. The core attributes included instructor practice variables, course structure variables, and dashboard design variables. The changes for each successive semester were based on the results found in the previous semester. A summary of the core attributes for each semester are included in Table 1.

Table 1

A Summary of the Core Attributes of Each Semester of Dashboard Implementation

Core Attributes	**Semester 1**	**Semester 2**	**Semester 3**
Instructor	• Advocated for video use • Ambiguous to whether quizzes were graded	• Advocated for students to complete homework problems	• Did not care if students watched videos or not • Periodic dashboard reminders in class
Course structure	• No due dates on quizzes • Unlimited attempts on quizzes • Easier quizzes with questions related to videos • Sent email notifying students of dashboard	• Soft due dates on quizzes • Unlimited attempts on quizzes • Release dashboard at start of semester • In person notification of the dashboard • Increased quiz question difficulty (exam-level questions)	• Strict due dates on quizzes • Naming system CHAMP • Limited number of quiz question attempts (3) • Presentation and periodic reminders of dashboard by teaching assistants
Dashboard design	• Included both content and skills recommenders • Content recommender was scatterplot design	• Only used content recommender • Removed skills recommender • Content recommender was scatterplot design	• Resources provided connected to unit-level feedback • Content recommender was unit-level feedback design

We first present the methods, data collection, results, and findings for each iteration (Fall 2015, Spring 2016, and Summer 2016) separately. We then present the combined results looking across all three iterations.

Participants

Participants for this study came from a first-year chemistry course (three different semesters and instructors) at a large private western university in the United States. Table 2 shows the number of participants from each iteration of the study.

Table 2

Outline of the Participants of This Study for Each Iteration

	Consent to survey	Take survey	Response %	Give dashboard data
Fall 2015	180	70	39%	62
Spring 2016	NA	NA	NA	92
Summer 2016	91	69	70%	120

Analysis Methods

We used design-based research to examine how student use of our dashboard changed across three different iterations of dashboard implementation in a higher education blended chemistry course. We compare the core attributes of each semester (course structure, instructor practices, and dashboard design) across each iteration and examine how the core attributes of each iteration affected student use of the dashboard. Student dashboard use was measured by the number of clicks within the dashboard system, the percent of students that accessed the dashboard during the course, and the number of power users, or students that used the dashboard frequently (greater than 50 clicks over the course of the semester). The number of clicks we used to define power users included the top 10% of students in terms of dashboard use. This allowed us to track students that frequently used the dashboard across each iteration. We also break down student dashboard use by final grade for our third iteration because it was the most successful iteration in increasing student dashboard use.

Survey responses were coded using an open coding approach. The resulting categories and response counts for each category are reported in the results section corresponding to the iteration the survey was given.

Iteration 1 Fall 2015

In the first launch of the dashboard, it was integrated into a general level chemistry course at a large private US institution and was taught by Professor A in Fall 2015. Professor A advocated for the use of the videos associated with the dashboard, requested that students watch the videos before class, and required that they take short quizzes about the key concepts in the videos. These videos were of high quality and were developed using funds obtained from the National Science Foundation. The quizzes were superficial, intending to check for understanding as opposed to representing exam-level difficulty. The dashboard was made available halfway through the semester, and the link to the dashboard was located adjacent to the links to the quizzes within the learning management system. This provided students easy access to the dashboard. In the first iteration of the dashboard design, it appeared as a scatterplot showing each concept as a point plotted on y (content mastery score) vs x (video use on concept), as shown in Figure 3.

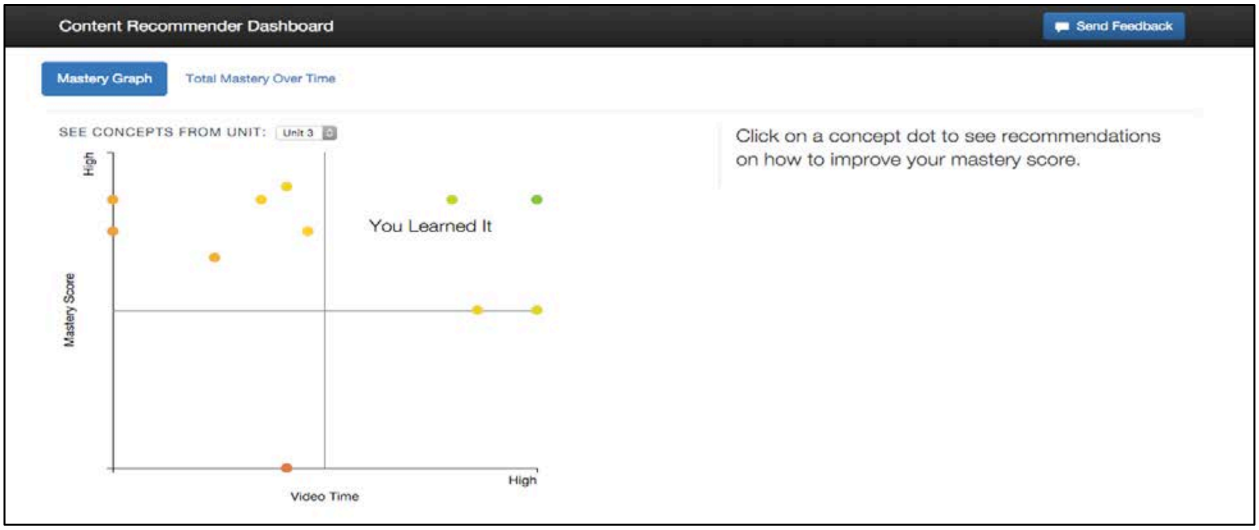

Figure 3. A screenshot of the learner dashboard used in Iteration 1.

In addition to the content recommender dashboard, the students were also provided access to a skills dashboard (see Figure 4). This dashboard was provided to students to help them be more reflective and aware of the way they were learning, with the hope that they would make changes to increase their study skills.

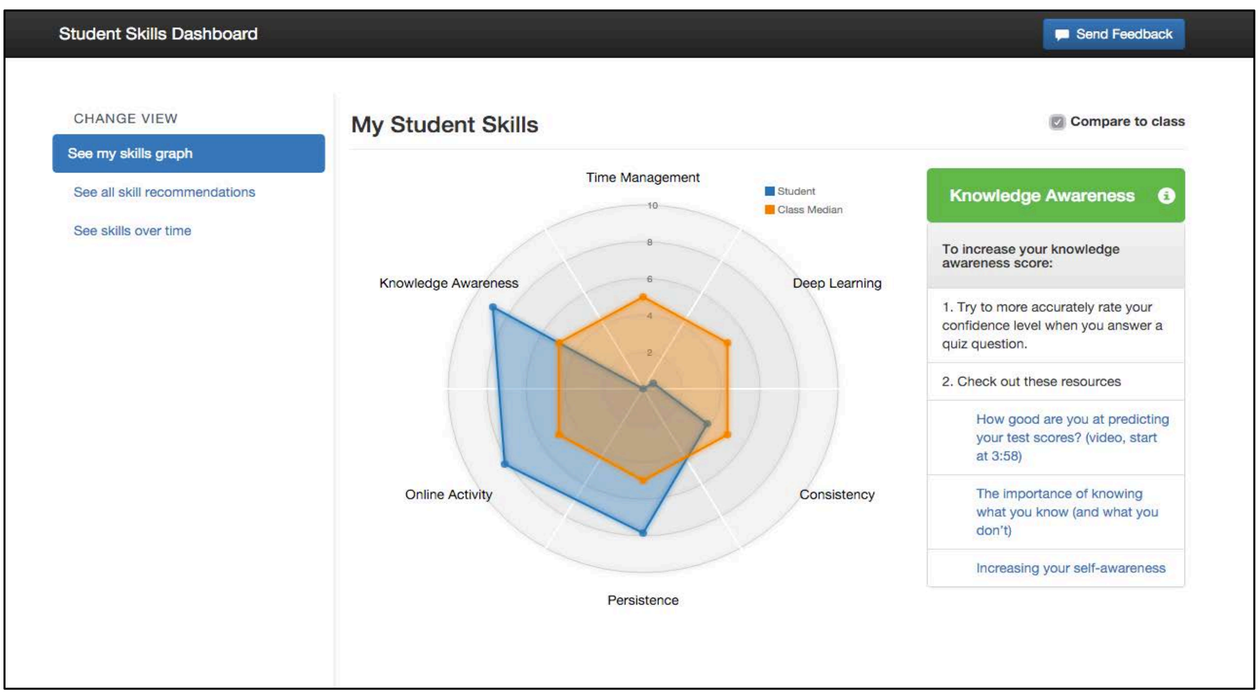

Figure 4. A screenshot of the skills recommender dashboard design used for the first iteration of our design-based research project.

This dashboard provided students with a radar chart representing their score on six different skills: time management, effort, consistency, persistence, online activity, and knowledge awareness (Bodily, Ikahihifo, Mackley, & Graham, in press, 2018). Each of these scores was calculated using the student click data within videos and quizzes. For example, effort was defined as the opposite of gaming the system. If a student manipulated the quiz system to get through an assignment as fast as possible, the effort score would decrease. Knowledge awareness was the combination of answer correctness and self-reported response certainty. If a student both answered correctly and felt confident about their answer, knowledge awareness would increase. If a student had a low score for a particular skill, they could click on the point and receive targeted recommendations to improve that skill.

Student use of the dashboard was collected and logged automatically by the system. The system tracked all student click actions within the dashboard. Sixty-two students consented to giving researchers access to their dashboard click data and used the dashboard.

A survey was given to students at the end of the semester to better understand their perceptions of the dashboard. The survey questions asked students what they liked about the dashboards, what they disliked about the dashboards, and what we could change to increase student use of the dashboards. There were 180 students who consented to take the survey, but with a 34% response rate, our final number of respondents was 70. The survey questions were designed to help us understand which dashboard design elements contribute to an efficient and effective student experience with the dashboard. This information helped us make course structure, teacher practice, and dashboard design changes that would be useful to students.

Fall 2015 Results and Discussion

Student use of the dashboard is reported in Table 3. “Users” used the dashboard at least once and “power users” had at least 50 clicks in the dashboard. Student use was much lower than anticipated. Only 56% of students accessed the dashboard at least once, which means almost half of the class never looked at the student dashboard. Potential reasons students did not use the dashboard include they did not have time to use it, they did not find it useful, and they had many other resources in the course (e.g. teaching assistant, office hours, help lab, etc.). Furthermore, only 13% of the class had consistent interactions with the dashboard.

Table 3

Student Dashboard Use Descriptive Data for Iteration 1 Fall 2015

	Iteration 1 Fall 2015
% users	56%
% power users	13%
Average clicks	23

We gave students a dashboard perception survey to help us contextualize the quantitative findings and better understand student use of the dashboard. We asked students what they liked about the dashboards, what they disliked about the dashboards, and what we could change to increase student use of the dashboards. Student feedback is grouped into the following three categories: (1) strategies to increase dashboard use, (2) dashboard comments regarding the efficiency of the dashboard, and (3) dashboard comments regarding the effectiveness of the dashboard. The survey results are summarized in Table 4 and described below.

Table 4

Descriptive Data on Topic Frequency from Survey Responses in Fall 2015

Category	Comment	# of comments
Increase Dashboard Use	Provide in person training	16
	Send email reminders	3
	Make dashboard required	2
	Provide more details about dashboard	4
Efficiency (+)	Appreciated unit-level feedback	9
	Save time by seeing low mastery concepts	4
	Liked videos organized by concept	2
Efficiency (-)	Interface confusing	6
	Integrate dashboard more with class	2
	Wanted to be able to search	3
Effectiveness (+)	High quality of study materials	6
	Required material was sufficient to attain mastery	14
Effectiveness (-)	Wanted more resources in general	6
	Wanted more textbook resources	2

Fall 2015 Summary

Based on student dashboard use and the end of course dashboard perception survey data, we decided to make some course structure and dashboard design changes. First, students used the content dashboard more than the skills dashboard because it was more relevant to helping them succeed in their chemistry course, so we decided to only provide the content dashboard in the next phase of our research. Second, due to technical difficulties, the dashboard could not be released until after the second exam in the course. This late release could be one reason students did not use the dashboards or were not aware of them. In our next phase (Spring 2016) we released the dashboard at the beginning of the semester. Third, the notifications for the first iteration of the dashboards were made by email instead of in person. Students often disregard course emails, which could explain why some students were not aware of the dashboard even though the link to the dashboard was listed right next to their assignment links. For the second iteration, we decided to discuss the dashboard in class to promote additional use. Fourth, the quizzes used in our first iteration were related to the recommended videos but were fairly easy. The feedback provided by the dashboard may not have been perceived as valuable by students because it was based on easy questions and was unable to meaningfully identify gaps in student content knowledge. To address this, the difficulty of questions was increased to compare to exam-level questions so students would care more about the data generated from the quizzes, and therefore the dashboard.

Iteration 2 Spring 2016

Taking these changes into account, the second deployment of the dashboard was performed in Professor B's general chemistry course in Spring 2016. In this instance, students were required to complete the quizzes, and those quizzes were revised to include problems of exam-level difficulty. However, the grading policy was lenient so students could make unlimited attempts at each question and could choose to show the answer without penalty—essentially grading was based on effort, not accuracy. In order to increase exposure to the dashboard, it was available the entire semester, the link was placed next to the link to the quizzes, and the videos were embedded within the dashboard. The dashboard still appeared as a scatterplot, and we only made minor design changes to the dashboard so a screenshot will not be provided here.

All student click actions within the dashboard were tracked and collected automatically by the system. There were 92 students (46% of the class) that consented to give researchers access to the dashboard clickstream data, and 51 students (55% of the class) accessed the dashboard. A survey was not given to students this semester because the results throughout the semester were comparable to the previous semester.

Spring 2016 Results and Discussion

Student use of the dashboard was tracked and is reported in Table 5.

Table 5

Dashboard Use Descriptive Statistics for the First Two Iterations

	Iteration 1 Fall 2015	Iteration 2 Spring 2016
% users	56%	55%
% power users	13%	20%
Average clicks	23	28

Users are defined as students who accessed the dashboard with at least one click. Power users are defined as students who had at least 50 clicks on the dashboard. The percent of students that used the dashboard (% users) stayed the same from fall semester, which indicates our class structure changes were not sufficient to motivate students to initially access the dashboard. However, the percent of power users and the average number of clicks both increased from fall, indicating students were using the dashboard more than previously. We hypothesize this is because we focused exclusively on the content dashboard instead of on both the content and skills dashboards. The content dashboard helps students to be more effective and efficient when compared with the skills dashboard, which explains why this focus increased student use.

Spring 2016 Summary

About halfway through the semester we realized student use of the dashboard was fairly comparable to the previous semester, meaning our class structure changes were not helpful in increasing initial student use of the dashboard. Because of this, we decided to redesign our dashboard to better fit the needs of the students. In addition, we made some significant class structure changes to try to increase initial student dashboard use. First, our dashboard was redesigned to show student mastery for each concept at the unit-level. Then, when a student clicks the concept, it provides practice problems, videos, and web resources to help students remediate their low mastery on the concept. Second, the exam-level questions remained in the quizzes, but the number of attempts were limited to three per question. We hoped this higher stakes environment would provide better data for students because there is a greater incentive to figure out problems rather than guess. Third, because many students were still not using the dashboard, we discussed and presented a demo of the dashboard in class as well as in recitation (class on Tuesday and Thursday with a teaching assistant). Fourth, we had the teaching assistants in the course periodically discuss the benefits of the dashboard along with how to use it so students would be informed. Finally, to help students remember the quizzes, videos, web resources, and dashboard, we decided to give the system a name: Chemistry Help and Mastery Problems (CHAMP).

Iteration 3 Summer 2016

For the third deployment of the dashboard, Professor C required students to complete quizzes which had limited attempts and were graded according to accuracy, not effort. The dashboard was redesigned to a bar chart format (see Figure 5), where students could see their performance mastery score for each topic within the unit and click on that topic to reveal additional resources such as extra practice questions, videos, and links to a free, open, online textbook, now called LibreTexts (https://chem.libretexts.org/).

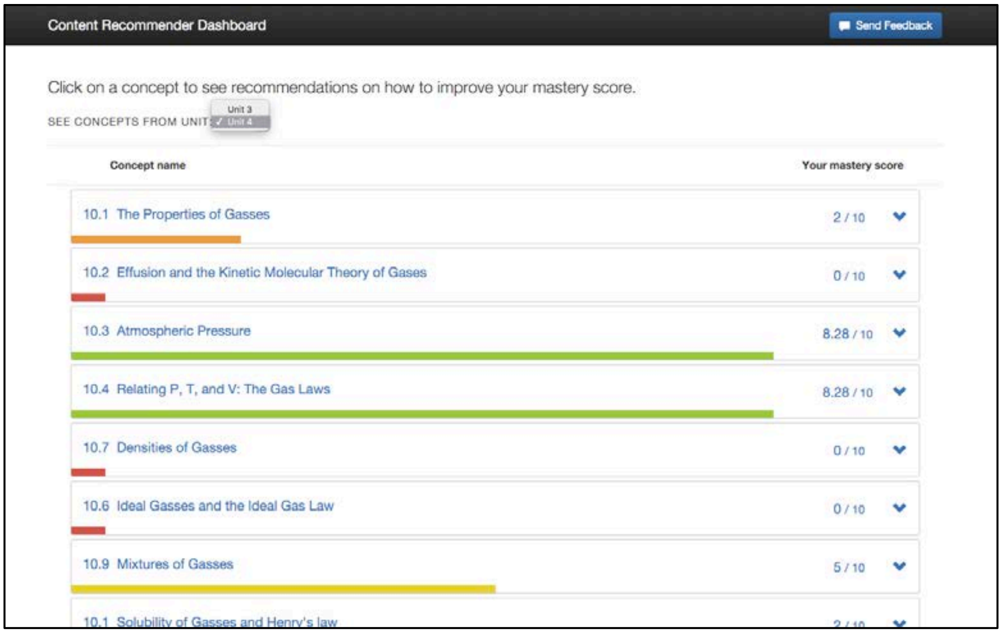

Figure 5. A screenshot of the content dashboard design for the third phase of our design-based research project.

In addition to the dashboard redesign, we attended each recitation section of the course to demo the dashboard system at the beginning of the semester, trained the teaching assistants on the use of the dashboard, and encouraged Professor C to mention the dashboard as a valuable tool to use to study for exams. Student use of the dashboard was tracked automatically by the system. The system tracked all student click actions within the dashboard. There were 120 students (128 in the class) who consented to allow us to have access to the dashboard click data.

A survey was given to students to better understand their perceptions of the dashboard. There were 91 students who consented to take the survey, and 70% (n = 69) completed the survey. The survey questions were designed to help us understand what dashboard features students liked, disliked, and requested for future implementation. This information helped us understand what course structure, teacher practices, and dashboard design changes were useful to students.

Summer 2016 Results and Discussion

Student use of the dashboard was tracked and is reported in Table 6. Users used the dashboard at least once and power users had at least 50 clicks in the dashboard. The percent of users in the dashboard increased from 54% in semester 2 to 73% in semester 3, the percent of power users increased from 20% in semester 2 to 24% in semester 3, and the average number of clicks increased from 28 in semester 2 to 36 in semester 3. These results suggest that the course structure, teacher practices, and dashboard design changes may have been helpful in increasing student use of the dashboard.

Table 6

Descriptive Statistics for Student Use Across All Three DBR Iterations

	Iteration 1 Fall 2015	Iteration 2 Spring 2016	Iteration 3 Summer 2016
% users	56%	55%	73%
% power users	13%	20%	24%
Average clicks	23	28	36

Because of the increases in student use during iteration 3, we broke down the results from semester 3 by student final letter grade. The fraction of users who are power users is the percent power users divided by the percent users. These results are presented in Table 7.

This more detailed breakdown highlights that the students who finish with a “C” have the greatest fraction of users who are power users. This means that if you finished the course with a “C”, you were more likely to use the dashboard more frequently when compared with other students. It is also interesting to note that the D, F, and W students (students that received a D grade, F grade, or Withdraw grade) had the lowest percent users and percent power users, suggesting that these students do not initially access nor continue to access the dashboard resource as much as the other students. Lastly, the "A" students had the highest percent users, suggesting that "A" students are more likely to explore potential resources to evaluate whether they will help student effectiveness or efficiency. Many of these students may have decided the dashboard would not be useful to them, so the percent of power users for "A" students was comparable to the rest of the groups. This could be because high achieving students were already succeeding in the course, so they did not need a tool to help them identify or remediate their knowledge gaps.

Table 7

Detailed Descriptive Statistics for Learner Dashboard Use During Iteration 3

Final Grade	N	Average Grade	Average Clicks	Percent Users	Percent Power-users	Fraction of Users who are Power-users
DFW	21	56.7	28.0	61.9%	19.0%	0.31
C	22	76.0	42.0	72.7%	36.4%	0.50
B	49	85.0	36.5	73.5%	22.4%	0.31
A	27	92.4	38.6	81.5%	22.2%	0.27

Throughout the semester we noticed a greater percentage of students were using the dashboard and that students were using the dashboard more frequently. Because of this, a survey was given to students at the end of the semester to evaluate the dashboard. The survey questions are presented below along with a discussion of the findings for each question. A table summary of the survey responses can be seen in Table 8.

Table 8

Descriptive Data on Topic Frequency from Survey Responses in Iteration 3

Category	Comment	# of comments
Effectiveness (+)	Extra practice quizzes	21
	High quality videos	21
	Unit-level feedback	11
	Reviewing concepts	9
	Test preparation	3
Effectiveness (-)	Technical difficulties	20
	Insufficient materials	8
Efficiency (+)	Organized and easy to use	17
	Extra practice problems	14
	Track proficiency	10
	Access to open textbook	5
Efficiency (-)	Lack of time	21
	Preferred other resources	13
	Did not see a need for it	8

Summer 2016 Summary

The third iteration showed improvement in percent users, percent power users, and average clicks per student when compared with previous semesters. This shows that the course structure, teacher practices, and dashboard design changes may have been effective at increasing student use. The dashboard was used more under these conditions and we believe it is because (1) the quality of the data input was the highest (quizzes were required, graded, and of exam-level difficulty), (2) the dashboard was discussed more frequently as a helpful tool, and (3) the design of the dashboard was the most intuitive. However, the percent power users category was still lower than we would expect. Only 24% of students are using the dashboard frequently throughout the semester.

Summary

The data collected from each of the three different semesters of dashboard implementation and student use can be seen in Table 9.

Table 9

Depiction of the Three Different Iterations in Our Design-Based Research Study

Semester 1	Semester 2	Semester 3
• Dashboard use data • Perception survey	• Dashboard use data	• Dashboard use data • Perception survey

Our goal across each semester was to increase the initial percentage of students that accessed the tool as well as the number of times each student accessed the tool. If students accessed the tool initially, we knew students were aware of the tool and at least looked at it. Then, if students continued to use our dashboard we have reason to suppose it was useful to them.

In order to understand student perceptions of our OLS dashboard, we conducted perception surveys. The surveys were sent to all students that consented to participate in the survey. We sent out evaluation surveys the first semester, Fall of 2015, to understand initial student perceptions, as well as the last semester, Summer of 2016, because the course structure, teacher practice, and dashboard design changes were more successful.

To summarize our iterative findings, we present a side-by-side comparison of dashboard use across each semester (Table 10).

Table 10

Side-By-Side Comparison of Student Dashboard Use Across Each Semester

	Iteration 1	Iteration 2	Iteration 3
% users	56%	55%	73%
% power users	13%	20%	24%
Average clicks	23	28	36

Iteration 2 showed slight increases in power users and average clicks, which is likely because we focused on the content dashboard, a dashboard system that helped students be more efficient and effective when compared with the skills dashboard. Then, we saw marked improvement from Iteration 2 to Iteration 3 on all dashboard use variables. These student dashboard use changes occurred after the following course structure, teacher practice, and dashboard design changes: (1) we limited homework quiz attempts to three instead of unlimited, (2) we increased visibility of the dashboard by providing frequent demos of the dashboard and giving the system a name (CHAMP), and (3) we made the dashboard design more intuitive. An intuitive learner dashboard design is essential to maximize student use as it lessens user frustration and increases student acceptance of the dashboard (Peng, 2009).

To summarize the course and dashboard changes made after each semester, they are described in Table 11.

Table 11

Summary of Changes Along with Suggested Changes for the Future

Changes after semester 1	Changes after semester 2	Suggestions After Semester 3
- Remove skills dashboard - Release dashboard at start of semester - In person notification of the dashboard - Increased quiz question difficulty	- Introduction of unit-level feedback - Resources connected to unit-level feedback - Limited number of quiz question attempts - Presentation and periodic reminders of dashboard by teaching assistants - Naming system CHAMP	- Change mastery score as students do more work in the system - Provide easy and difficult problems for each concept - Provide a class comparison tool to motivate students

Self-Determination Theory Support

The major findings from looking across all three iterations of our DBR study can be explained through the lens of self-determination theory (SDT). Ryan and Deci (2000) have explained that in a SDT context, a person needs certain basic needs met in order to achieve a certain level of intrinsic motivation. These needs are autonomy, competence, and relatedness. This design focused only on the aspects of autonomy and competence. Ryan and Deci (2000) claim that students who feel they have more control over their learning, or that have a choice in how or what they learn, are more likely to be self-motivated in their learning. In addition, they claim that if the need to master or be competent at something is fulfilled, intrinsic motivation will increase. The dashboard design and class structure changes that were made throughout each iteration of our DBR study can be explained within the context of student autonomy and student competence.

After the first iteration, we realized students were not using the skills recommender dashboard and decided to only focus on the content dashboard. This made sense because students want a tool that will help them become competent as quickly as possible. The skills dashboard was not as relevant to their success in the course, and therefore was used less than the content dashboard. In addition, the content dashboard provided students with resources that allowed them to choose how they wanted to learn, supporting student autonomy (Katz & Assor, 2007).

After the second iteration, we increased the visibility of the dashboard, made the dashboard design more intuitive, and increased the importance of the data feeding into the dashboard. All of these changes made using the dashboard more effective and efficient for students (Black & Deci, 2000). This allowed students to more easily choose how or if they will remediate gaps in their content knowledge (supporting student autonomy) and allowed them to do it more quickly (enabling student competence) (Katz & Assor, 2007).

After the final iteration, we saw moderate improvement in dashboard use, but still only about one fourth of students used it frequently. Some studies have shown a majority of students will use optional course resources (Grabe & Christopherson, 2008; Chamala et al., 2006), while others have found that only a small minority of students choose to focus on understanding and mastery by going beyond what is required (Liberatore, 2011; Richards-Babb, Drelick, Henry, & Robertson-Honecker, 2011), depending on how useful the system is to students. Future research in this area should determine the optimal balance between student autonomy and teacher control in order to maximize student use of learning resources. Another line of research could investigate the effect of a dashboard connecting students to online tutors in an online course to help students remediate their knowledge gaps.

Learner Dashboard Adoption Theory

Strategies to increase student use of learner dashboards can be divided into two main areas: student trust in the system and instructor adoption. If students have high trust in the system and instructors include the system in a meaningful way in the course, students will use the learning dashboard. In Table 12 and Table 13, we provide recommendations for ways to increase student trust and improve instructor adoption.

Table 12

Recommendations to Increase Student Trust in a Learner Dashboard

Student Trust
1. Conduct pilots to take care of technical issues in implementation
2. Make sure the dashboard is easy to use through usability testing
3. Ensure students understand what the visualizations and recommendations in the dashboard mean
4. Make sure students know how to use the dashboard effectively
5. Put high quality data students care about in the dashboard
6. Put high quality resources to remediate knowledge gaps in the dashboard
7. Ensure the dashboard helps students to be more efficient and effective

Table 13

Recommendations for Instructors to Effectively Adopt a Learner Dashboard into a Course

Instructor Adoption
1. Teach students how to use the dashboard effectively
2. Remind students throughout the course why the dashboard is helpful
3. Use the dashboard system meaningfully in the course
4. Align the dashboard with course pedagogies and teaching strategies
5. Ensure the dashboard is integrated into the normal coursework flow

Limitations

There are differences between the three semesters that were not accounted for in our analysis. Though the same content was covered in all three semesters, each professor had the liberty to teach content in the order, manner, and structure they pleased. Each professor also chose to utilize the dashboard in a unique way tailored to their class structure. In addition, each professor offered different exams and homework. It should also be noted that differing semesters included different course lengths. The courses offered in Fall 2015 and Spring 2016 were given over a period of 16 weeks, while the class offered in Summer 2016 covered the same content but with a duration of 8 weeks. While these changes are potential limitations to our study, we believe our mixed methods design-based research approach helped us improve course design and learner dashboard design to foster increased student use.

Another possible limitation is that our institution has a fairly homogeneous population. The research was conducted at a private, religiously affiliated university. Over 90% of students are from the United States, and only 16% of students come from minority groups. Different and more diverse populations of students may interact differently with the dashboard.

Implications for Conclusions

In this section, we discuss the conclusions for the article within the context of implications for research and implications for practice.

Research

Future research should investigate the effect of a dynamic mastery score (dashboard mastery level that changes as students work on extra problems) on student use when compared with a static post-quiz mastery score. This is important because a dynamic mastery score can help students see progress as they are attaining mastery, improving their level of competence (Own, 2010; Mampadi, Chen, Ghinea, & Chen, 2011). This work should also examine additional types of learner dashboards beyond a content dashboard and a student skills dashboard. Open learner model researchers have investigated negotiated student models, where students can negotiate with the system to prove what they know, and interactive student models, where students can interact in some way with the knowledge representation available in a learner dashboard (Kerlyl, Hall, & Bull, 2007; Woolf, 2009). These methods have been applied in an open learner model context and could be an effective way to increase student autonomy in a learning analytics dashboard context. Another aspect of a dashboard that has not been evaluated alongside student use is a class comparison feature. When students are able to compare their scores with those of their class, they may react differently depending on their learner characteristics (Aguilar, 2018). For example, they may be motivated to improve or stay above the class average, feeling competent. Conversely, they may be demotivated, lacking competence, if they do not think there is a chance for them to catch up to their peers.

Beyond dashboard design changes, there are some course structure changes that could be effective at increasing student use of a dashboard. Requiring students to access the dashboard at least once would give all students the opportunity to evaluate whether they would like to continue using the dashboard or not, which may increase student dashboard use throughout the semester (Hatziapostolou & Paraskakis, 2010). Future work should also examine how limiting attempts on homework problems to one or two attempts affects the way in which students value the data in the dashboard.

Our findings indicate there may be trends in the types of students that access dashboards. Iteration 3 in our study showed that it was the "C" students that were most likely to continue to use the dashboard. This is interesting because one would hope the dashboard would improve performance of "C" students into "B" or "A" students, but there is no way of knowing if the "C" students, without the dashboard, would have ended up as "D" or "F" students. Future research should investigate how to tailor a dashboard to this student population. Specifically, research should look into how to increase the number of "C" and failing students that access and continue to access the dashboard. Additional student information that may influence student dashboard use includes learner characteristics, demographic data, and prior learning achievement.

Future iterations of our DBR study should investigate how student use of the dashboard changes as a result of (1) adding exam scores or additional homework scores to the dashboard,

(2) making the student mastery score change as students complete extra practice problems, (3) adding a class comparison feature to show how students compare to others in the class, and (4) requiring students to visit the dashboard at least once for course credit.

Practice

Chemistry OLSs are commonly used to give students immediate feedback on their problem-solving skills, allowing students to attempt the same problem or assignment multiple times, with responsive support to scaffold learning. This strategy is helpful in bringing students closer to mastery but may give them a false sense of confidence. A mastery score that takes into account both accuracy and number of attempts may be a better tool for students as they prepare to take exams, which typically only allow one attempt. Furthermore, providing unit-level feedback based on core concepts can be useful above and beyond scores on assignments, which can be difficult for students to deconstruct into the appropriate course topics. Making this feedback visual is a powerful way to increase its interpretability. The dashboard does not give students any more information than they already had, but it presents information in a way that can guide student efforts toward those concepts that are weakest.

When unit-level feedback is provided, it is important to also include resources that support students, improve their performance, and allow them to evaluate their progress. Identifying concepts that the student has not yet mastered is a key factor in helping them direct their learning efforts most efficiently. When mastery information is complemented by instructor-approved resources, such as links to videos, references to online texts, and additional practice problems, it further helps direct student efforts toward meaningful learning.

Chemistry practitioners should track students as they use autonomous tools in OLSs to be more aware of how they are being used by students. If these optional tools are expensive and time consuming to create, they should be properly evaluated to make sure they are useful to students. If students are not using them, course changes can be made to increase student use of these tools. Students often do not engage with feedback or learning materials when it is optional, even if it would help them to succeed. Practitioners and researchers should work together to determine how to encourage or support students in engaging with feedback in autonomous learning environments.

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DISSERTATION CONCLUSION

In the first section, I presented a literature review that reviewed 93 articles about student-facing learning analytics reporting systems and educational recommender systems. In that review, we found that the learning analytics reporting field is relatively new; there have not been many rigorous studies examining the effects of these systems on student outcomes; and many researchers report the final system in their articles, but fail to discuss the design and implementation processes.

To partially fill this gap, I presented the second article of my dissertation in section two. This article incorporated the best elements found from the literature review: we discussed the entire design and development process; we built the dashboard so it presented data in real-time to students; we included class comparison functionality; and we tracked students as they used the dashboard. Despite our efforts to build a tool that would be helpful to students, students did not use it much throughout the semester. The dashboard system was an optional activity, but we believed we could increase the implementation fidelity and adoption of the dashboard.

To do this, I presented article three of my dissertation in section three. This article was a design-based research study to investigate the effect of course structure, instructor practices, and dashboard design on student use of dashboard systems. We used design-based research across three iterations to investigate the previously mentioned core attributes. We found that we were able to increase student use of dashboard tools by (a) helping students to trust the dashboard system, (b) helping students to understand how and why to use the dashboard system, and (c) helping the instructor to more meaningfully include the tool in their course.

While learner dashboard systems have not had large effects on student outcomes, I believe that as the field matures and learns from more mature fields, such as the Open Learner

Model research literature, that learner dashboard systems will be able to (a) help students identify and remediate their knowledge gaps, (b) increase student effectiveness and efficiency in their studying, and (c) increase student intrinsic motivation by supporting student autonomy and competence.

To achieve these goals, we need learner dashboard research that (a) reports on the entire design and development process of the learning dashboard, (b) rigorously examines the effect of the dashboard system on student behavior, student achievement, and other student characteristics, (c) tracks and reports on student use of the dashboard system, (d) reports on rigorous usability and evaluation studies, (e) builds on the Open Learner Model research literature on negotiated student models and learner trust, (f) builds on additional theoretical constructs beyond self-determination theory and feedback, and (g) focuses on implementation fidelity and adoption, both from an instructor adoption perspective and from a student adoption perspective.

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