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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, 2014). 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 traditional 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 them with information regarding student mastery and resource use so they 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 area of research focused on achieving this 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 their awareness of their own knowledge and to help them reflect on their learning in order to become better learners (Verbert et al., 2014).

Learning analytics dashboards have many advantages over other feedback methods: the system collects data unobtrusively and does not interfere with student engagement in the course, it automatically collects data without external intervention from instructors or course designers, and it 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**

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 Author (2017), the authors found sixty-two student-facing dashboard articles. Of the systems discussed in those articles, only thirteen included both visualizations and recommendations (see Table 1). 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.
### Table 1.

**A Summary of Findings from Author (2017)**

<table>
<thead>
<tr>
<th>Citations</th>
<th>Finding</th>
<th># of articles</th>
<th>% of articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anaya, Luque, &amp; Peinado, 2016; Ott, Robins, Haden, &amp; Shephard, 2015; Feild, 2015; Harrer &amp; Göhnert, 2015; Govaerts, Verbert, Duval, &amp; Pardo, 2012; Ruipérez-Valiente, Muñoz-Merino, &amp; Kloos, 2013; Laffey, Amelung, &amp; Goggins, 2014; Jugo, Kovačić, &amp; Slavuj, 2014; Govaerts, Verbert, Klerkx, &amp; Duval, 2010; Ruipérez-Valiente, Muñoz-Merino, Leoný, &amp; Kloos, 2015; Muldner et al., 2015; Ferguson &amp; Shum, 2012; Iandoli, Quinto, De Liddo, &amp; Shum, 2014</td>
<td>Included both visualizations and recommendations</td>
<td>13</td>
<td>21%</td>
</tr>
<tr>
<td>Santos, Verbert, Govaerts, &amp; Duval, 2013; Grann &amp; Bushway, 2014; Kim, Jo, &amp; Park, 2016; Santos, Verbert, &amp; Duval, 2012; Ott et al., 2015; Tervakari, Silius, Koro, Paukkeri, &amp; Pirttila, 2014; Hatziapostolou &amp; Paraskakis, 2010; Muldner et al., 2015; Kuosa, 2016</td>
<td>Tracked student use of a learner dashboard</td>
<td>9</td>
<td>15%</td>
</tr>
<tr>
<td>Harrer, 2015; Park &amp; Jo, 2015; Kim et al., 2016; Santos, Govaerts, Verbert, &amp; Duval, 2012; Corrin &amp; de Barba, 2015; Ott et al., 2015; Harrer &amp; Göhnert, 2015; Olmos &amp; Corrin, 2012; Iandoli et al., 2014</td>
<td>Provided justification for visual design and information selection process</td>
<td>10</td>
<td>16%</td>
</tr>
<tr>
<td>Schmitz et al., 2009; Park &amp; Jo, 2015; Santos et al., 2012; Jeon, Yeon, Lee, &amp; Seo, 2014; McAuley, O’Connor, &amp; Lewis, 2012; Charleeer, Klerkx, Odiozola, Luis, &amp; Duval, 2013; Silius et al., 2010; Tervakari, Silius, Koro, Paukkeri, &amp; Pirttila, 2014; Silius, Tervakari, &amp; Kailanto, 2013; Hatziapostolou &amp; Paraskakis, 2010; Odiozola, Luis, Verbert, Govaerts, &amp; Duval, 2011; Holman, Aguilar, &amp; Fisherman, 2013; Ferguson &amp; Shum, 2012; Iandoli et al., 2014</td>
<td>Included both class comparison and interactivity features</td>
<td>15</td>
<td>24%</td>
</tr>
<tr>
<td>Arnold &amp; Pistilli, 2012; Melero, Hernández-Leo, Sun, Santos, &amp; Blat, 2015; Ott et al., 2015; Feild, 2015; Manso-Vázquez &amp; Llamas-Nistal, 2015; Arnold, 2010; Jugo, Kovačić, &amp; Slavuj, 2014; Ruipérez-Valiente, 2015; Muldner et al., 2015</td>
<td>Collected resource use, time spent, and assessment data</td>
<td>10</td>
<td>16%</td>
</tr>
</tbody>
</table>
LADs commonly track students as they interact with resources throughout a course. However, LADs rarely track click-level student use of the dashboard tool. This is important because whether students use the dashboard or not can impact the results of the evaluation or implementation of a dashboard system. Author (2017) found that nine systems out of the sixty-two student-facing LADs in their study tracked student use of the dashboard system (Table 1). 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. Author (2017) found that ten systems out of the sixty-two student-facing LADs in their study provided justifications for the visual design chosen and the information selection process (Table 1). Being transparent about the iterative design and development process that occurs before the final product could increase robust research on LAD, 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 (Author 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. Author (2017) found that fifteen out of the sixty-two student dashboard articles they found discussed systems that had both class comparison and dashboard interactivity features (Table 1). 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. Author (2017) found that of the sixty-two student dashboards in their study, ten dashboards collected all three types of data (Table 1). 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, 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 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.
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 Learning Tools Interoperability (LTI) compliant. LTI is a learning tool specification that facilitates single-sign-on access within educational applications (https://www.imsglobal.org/activity/learning-tools-interoperability). We then developed an xAPI backend to enable data collection within the quiz application. The xAPI standard is a data format 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/). 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 Learning Record Store (LRS) called Learning Locker (https://learninglocker.net/). An LRS is a database that stores xAPI statements sent from different learning applications (http://tincanapi.com/learning-record-store/). 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 2.

Table 2.

*Data Points Collected or Calculated in our Analytics System.*

<table>
<thead>
<tr>
<th>Video Analytics</th>
<th>Quiz Analytics</th>
<th>Dashboard Analytics</th>
</tr>
</thead>
<tbody>
<tr>
<td># of plays</td>
<td># of question attempts</td>
<td># of dashboard views</td>
</tr>
<tr>
<td># of pauses</td>
<td>Time spent on quizzes</td>
<td>Time spent in dashboard</td>
</tr>
<tr>
<td># of video seeks</td>
<td># of quizzes attempted</td>
<td># of video suggestion clicks</td>
</tr>
<tr>
<td># of play rate changes</td>
<td>Average confidence level</td>
<td># of quiz suggestion clicks</td>
</tr>
<tr>
<td>Average video speed</td>
<td>Max number of attempts</td>
<td># of unique visits to dashboard</td>
</tr>
<tr>
<td># of volume changes</td>
<td>Max time on a quiz</td>
<td></td>
</tr>
<tr>
<td>Average volume setting</td>
<td>Score on quiz</td>
<td></td>
</tr>
<tr>
<td># of mute/unmute</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of max/minimize</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time spent on videos</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of videos watched</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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 is presented at the unit-level, which allows students to study more strategically as they can easily see their knowledge gaps and know where they should spend their time to improve their content mastery (Bangert-Drowns, Kulik, Kulik, & Morgan, 1991). Furthermore, students are presented with recommendations of videos, extra practice problems, and internet textbook links, if they click on a concept, to help them remediate their knowledge gaps. These recommendations are action items for students that allow them to act once they have recognized their knowledge gaps (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. Verbert et al. (2013), in the earliest review of dashboard studies, stated that this self-knowledge provides benefits including fostering insight, increasing self-control, and promoting good behaviors.

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 traditional 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 & Cavanaugh, 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. In our design process, we were thoughtfully eclectic by constantly soliciting feedback from users, which allowed us to make adjustments we felt were needed based on our practical experience and agency. 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. By frequently soliciting feedback throughout the design process and then conducting focus groups and surveys as a more summative evaluation, we were able to merge the theoretical and practical domains into a concrete dashboard tool. The last benefit of a practice-centered approach is sharing practices. By focusing on practice and carefully analyzing the successful pieces of a design, good elements of design can emerge that can be used in future designs (Wilson, 2013).

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.

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

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). 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.

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

The recommendations view (see Figure 3) is where students go if they clicked on the mastery bar chart. 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) using a think-aloud protocol. Students and faculty were instructed to click through the dashboard prototype, voicing aloud what they were thinking, what they were trying to accomplish, and what concerns they had about the prototype. 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.
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) using the same procedures as outlined earlier. 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 had to scroll within the recommendations tab and scroll down to see all of the concepts (scrolling within a scrolling page was difficult to navigate), (2) users could not see video usage in relation to assessment data, and (3) the drop down recommendations bar was a little too cluttered. These weaknesses were addressed in the third version of our content recommender. We also discovered similar strengths to the previous

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

![Content Recommender Dashboard](image)

**Fig. 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 users 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 on their behaviors in the course, become more aware of the way in which they learn, and change their learning behaviors to match with their goals in the course (Shute, 2008; Hacker, Dunlosky, & Graesser, 1998).

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

Fig. 7 Total mastery over time view for the content recommender dashboard
We again solicited informal student and faculty feedback (n=10) using the same procedures outlined earlier. 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. This 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).

![Fig. 8 The simple view of the student skills recommender version one](image)
We solicited informal feedback from faculty and students (n=10) using the same procedures outlined earlier 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 traditional 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). 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.

![Student Skills Dashboard](image)

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

Informed consent was obtained from all individual participants included in the study. Focus groups were conducted with consenting students. 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 et al., 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. There were two coders that each coded the qualitative responses. If the coders disagreed on any particular code, it was discussed until an agreement was made. The student learning analytics needs that emerged from the focus groups are summarized in Table 3.
Table 3.

A Summary of Focus Group Themes

<table>
<thead>
<tr>
<th>Category</th>
<th>Number of statements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Useful features</td>
<td>39</td>
</tr>
<tr>
<td>Requested features</td>
<td>32</td>
</tr>
<tr>
<td>Course content</td>
<td>28</td>
</tr>
<tr>
<td>Bad features</td>
<td>17</td>
</tr>
<tr>
<td>Frequency of use</td>
<td>15</td>
</tr>
<tr>
<td>Course synchronization</td>
<td>11</td>
</tr>
<tr>
<td>Comparison between dashboards</td>
<td>7</td>
</tr>
</tbody>
</table>

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). 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).
Fig. 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)

Fig. 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)

**Research Implications and Future Research**

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 (Author, 2017).

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 keeps them motivated and makes them want to engage with it. 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. Author (2017) reported that only a small percentage of articles in their systematic literature review reported on research experimental results and used 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 randomly split a class into treatment and control conditions 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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