Developing a Teacher Dashboard For Use with Intelligent Tutoring Systems

Vincent Aleven Franceska Xhakaj Kenneth Holstein Bruce M. McLaren

Human-Computer Interaction Institute
Carnegie Mellon University
Pittsburgh, PA
USA

{aleven, francesx, kjholste, bmclaren}@cs.cmu.edu

ABSTRACT

Many dashboards display analytics generated by educational technologies, but few of them work with intelligent tutoring systems (ITSs). We are creating a teacher dashboard for use with ITSs built and used within our CTAT/Tutorshop infrastructure: an environment for authoring and deploying ITSs. The dashboard will take advantage of the fine-grained interaction data and derived analytics that CTAT-built ITSs produce. We are taking a user-centered design approach in which we target two usage scenarios for the dashboard. In one scenario, a teacher uses the dashboard while helping a class of students working with the tutoring software in the school's computer lab. In the other, the teacher uses the dashboard to prepare for an upcoming class session. So far, we have completed a Contextual Inquiry, ideation, Speed Dating sessions in which teachers evaluated story boards, usability testing, and a classroom study with a mocked up version of the dashboard with real data from the teacher's current classes and students. We are currently analyzing the data produced in these activities, iterating on the design of the dashboard, and implementing a full version of the dashboard. Unique characteristics of this dashboard may be that it leverages fine-grained interaction data produced by an ITS and that it will be fully integrated with an ITS development and deployment environment, and therefore available for use with many ITSs.

CCS Concepts

• **Applied computing~Interactive learning environments**

Keywords

Intelligent tutoring systems, learning analytics, user-centered design, dashboards, blended learning, student modeling.

1. INTRODUCTION

In the field of learning analytics, dashboards are often viewed as an important way in which data about students' learning processes can be used to make instruction more effective [18,48]. Dashboards are often used in college-level online courses or blended courses (e.g., [32]). They have also been used to support computer-supported collaborative learning scenarios [24,38], learning with mobile devices [16,25], and tabletop instructional technology [34,44].

Many papers describe dashboard designs and present evidence that users found these designs useful [1,17,22,39]. However, there has been almost no empirical work that shows how teacher dashboards influence student learning. Some studies came close. For example, Lovett, Myers, and Thille [32] showed that a redesigned college-level online statistics course led to greater *and* more efficient learning, compared to the original course. The redesign involved adding a new dashboard but the course was changed in other ways as well, so the better results cannot be attributed solely to the dashboard.

We are creating a dashboard for teachers who use intelligent tutoring software in their classrooms. Intelligent tutoring systems (ITSs) have led to improved learning outcomes in many domains [28,33,40,45-47] but often are not designed to involve teachers. ITSs might be even more effective if they were designed to not only help students directly, but to provide data to teachers to help them help their students. In fact, they already produce a wealth of sophisticated analytics, based on student modeling methods, that might be useful for this purpose. In our current project, we take a user-centered design approach to create a teacher's dashboard for intelligent tutoring software, focusing on realistic classroom scenarios.

The work differs from past work on teacher dashboards in that it focuses on intelligent tutoring technology rather than typical online course materials. This difference is significant because ITSs record student interaction data at a very fine-grained level, enabling advanced student modeling. These models often capture aspects of student knowledge, affect, metacognition, and other variables. However, there are many interesting open questions as to how such a dashboard can be designed to fit with classroom practice and whether teachers can take advantage of it to help their students learn more effectively.

Our project focuses on the following research questions:

1. What up-to-the-minute data about student learning that ITSs can provide is helpful to teachers and how can it best be presented in an actionable manner?
2. How do teachers use actionable analytics presented in a dashboard to help their students?
3. Do students learn better when their teacher monitors a dashboard and uses it to adjust the instruction?

In the current paper, we report on the steps taken so far in our user-centered design process and on an experimental study for

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which we have completed data collection. At the time of this writing, we have preliminary answers for the first two questions, and are still working on the third.

2. BACKGROUND: THE CTAT/TUTORSHOP ENVIRONMENT FOR ITS RESEARCH AND DEVELOPMENT

The dashboard we create will be integrated in our general infrastructure for ITS authoring and deployment, the CTAT/Tutorshop infrastructure [7,8]. The CTAT tool suite makes it possible to develop intelligent tutors without programming and to deploy and use them on the web. It is proven and mature, having been used by over 600 authors for projects of various levels of ambition and in a variety of domains. Tutors built with CTAT have been used in at least 50 research studies, most of which took place in real educational settings. The Tutorshop is a learning management system specifically designed to support classroom use of CTAT-built ITSs. It provides teachers with tools for creating class lists, assigning work (i.e., tutor problem sets) to students, and viewing reports on student progress and learning. It hosts a variety of tutors, including Mathtutor [6,9], Lynnette [30,31,49] (see Figure 1), and tutors for genetics problem solving [20], stoichiometry [36,37], decimals [23,35], and fractions [41-43]. Tutorshop is implemented in Ruby on Rails with a database in MySQL. Tutors built in this infrastructure are compatible with DataShop, a large online service that provides data sets and tools for researchers in educational data mining (EDM) [26].

Figure 1. Lynnette is an intelligent tutoring system for basic equation solving, implemented within the CTAT/Tutorshop architecture.

Building on the CTAT/Tutorshop infrastructure facilitates the development of the dashboard, for two reasons. First, any tutor built within this infrastructure generates a wealth of data from which informative analytics can be calculated. Second, the infrastructure is geared towards feeding back information to teachers, though in elaborate reports rather than the use-specific, actionable form we foresee for the dashboard. Importantly, the dashboard and the newly developed learning analytics will become part of the CTAT/Tutorshop infrastructure. Thus, they will be available in many CTAT-built tutors.

In our research, we will use a tutoring system called Lynnette, designed to help 7th and 8th grade students learn basic skill in equation solving [30,31,49] (see Figure 1). As ITSs typically do, Lynnette supports learning by doing. It presents problems that are matched to each individual student's evolving skill level. It also provides detailed, step-by-step guidance as students solve these problems. That is, it gives feedback as students attempt to take steps in each problem. Also, upon request, it gives strategic hints suggesting what transformation to try next, even if the student follows an unusual strategy. Lynnette is flexible enough to follow along with students regardless of what sequence of reasonable transformations they try as they solve equations. Lynnette has been shown in five classroom studies to help students learn effectively [29-31,49].

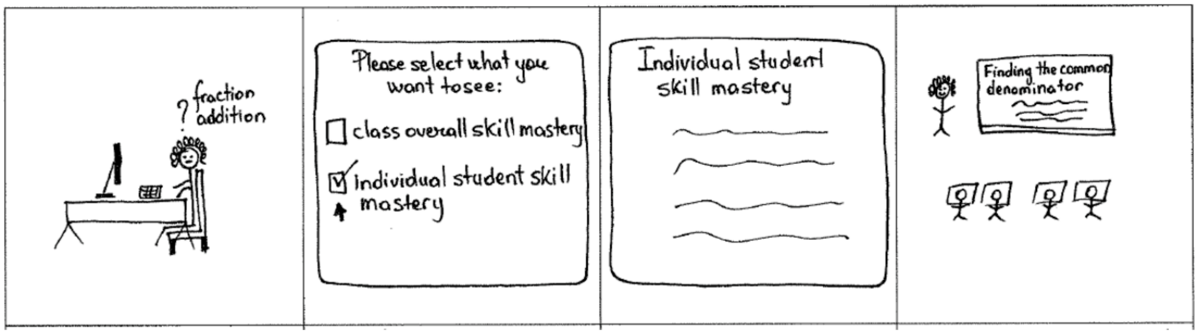
The idea to build a dashboard was inspired by an informal observation by Yanjin Long, a former PhD student at our institution, during one of her classroom studies with Lynnette. During a session in which middle-school students used Lynnette in their school's computer lab, the teacher of this class, who was walking around in the lab to keep a close eye on how her students were progressing with the tutoring system, repeatedly saw her students make the same error. Although the tutoring software flagged this error and helped students recover, the teacher wisely decided that more was needed. Perhaps key conceptual knowledge was missing. Right then and there, she inserted a brief mini-lesson in front of the lab's white board, explaining not just the correct procedure (as Lynnette would do) but highlighting conceptual background knowledge regarding why this procedure is the way it is and why the error is wrong. This illustrates one of the scenarios for which we are designing the dashboard. The dashboard may make this kind of scenario more frequent and more effective.

3. USER-CENTERED DESIGN

We are implementing a user-centered design process in which we identify needs of teachers in different usage scenarios and design to address these needs. We also explore the utility of analytics currently used for research but not, typically, in practice, such as learning curves [26], graphs that track the gradual increase in correct execution of targeted knowledge components over successive practice opportunities We focus on dashboard use within blended courses in which students use intelligent tutoring software several times a week, and in which the remaining classroom time is spent on lectures, group work, and seat work. This approach is typical of Cognitive Tutor courses, a type of ITS that is widely used in American middle schools and high schools [27]. Within this broader context, we focus on two specific scenarios in which a teacher uses the dashboard, namely, exploratory/reflective use of analytics to inform decisions about what to do during subsequent class periods (we refer to this as the "next-day" scenario) as well as real-time decision support, in which the dashboard displays up-to-the-second analytics as a class of students is working (in the school's computer lab) with the tutoring software (we refer to this as the "on-the-spot" scenario). So far, we have carried out the following activities:

- Contextual Inquiry with teachers
- Interpretation Sessions and building work models, followed by creating an Affinity Diagram
- Speed Dating to explore design ideas captured in storyboards
- Developing prototype designs.

Storyboard_1: Does overall skill information or individual skill information help you make decisions as you prepare for the next class?



Mrs. Byrd is preparing for a lecture on fraction addition, but she is not entirely sure what to cover in class.	The dashboard asks Mrs. Byrd if she wants to see *class overall skill mastery* or *individual student skill mastery* for the skills of (1) finding the common denominator and (2) converting the numerators to a proper form. These are skills related to the topic she wants to discuss in class. Mrs. Byrd chooses the second option.	Mrs. Byrd sees that most of the class has mastered the skill of converting the numerators to a proper form, but few students have mastered the skill of finding the common denominator.	Mrs. Byrd decides to go over finding the common denominator during the next class meeting, but decides not to discuss converting the numerators to a proper form.

Figure 2. A storyboard depicting the focus question (at the top), the storyboard images (the first row) and the description of each image and the story (second row)

- Prototyping sessions with teachers
- Classroom experiment in which a mocked up dashboard was fueled with real data from the teacher's current classes and students.

A key design challenge is figuring out which of the many analytics that ITSs produce will be most useful for teachers, as well as how they can be presented to teachers in an actionable way. We explore this question throughout the user-centered design process. Below we list possible analytics, to illustrate the range of possibilities. This list was drawn up based on our knowledge of teacher reports in Mathtutor and Cognitive Tutor, our knowledge of the literature on learning analytics and educational data mining, and suggestions from two teachers. Some of these analytics can be distilled or aggregated in a straightforward manner from the interaction stream with an ITS. Others require more sophisticated detectors or metacognitive tutor agents. However, all items listed below are realistic in that they have been demonstrated in prior ITS or EDM work.

- Progress through problem units in the tutoring software
  - Overall progress (e.g., list of units completed)
  - Progress rate (e.g., problem-solving steps completed per unit of time)
  - Progress during the current session or past sessions
  - Progress since a particular benchmark date, (suggested by a teacher whom we interviewed)
- Skill mastery and rate of learning
  - Learning curves [26]
  - Skills mastered [19]
  - Skills students are about to start working on
  - Most/least difficult skills, determined through learning curve analysis [26]
  - "Wheel spinning," that is, not learning a skill despite repeated practice [13]
  - Generality of knowledge learned – statistical fit with different knowledge component models may indicate whether students make or miss key generalizations such as treating constant and variables term the same where appropriate [3,15]
- Learning behaviors
  - Effective help use [4,5]
  - Frequent use of bottom-out hints (gaming the system) [2,12]
  - Being on/off task [11]
  - Being frustrated or bored frequently (affect) [21]
  - Effort (e.g., evidence of steady work without maladaptive strategies) [10]
  - Being stuck on a problem for a long time (brought up by one of the interviewed teachers)
- Where are the challenges for students?
  - Which problem types, problems, or steps are hardest? (suggested by one of the interviewed teachers)
  - Which problems are harder than the most similar problems?
  - Which error types are most frequent across problems?

3.1 Contextual Inquiry

We started with Contextual Inquiry sessions to investigate how teachers currently use data in order to inform their pedagogical decisions. Contextual Inquiry is a form of semi-structured interview within the context of a specific task [14]. The participants were 6 middle school teachers in 3 schools. We collected a total of 11.5 hours of video data. Some of our main findings were that teachers use data extensively, often

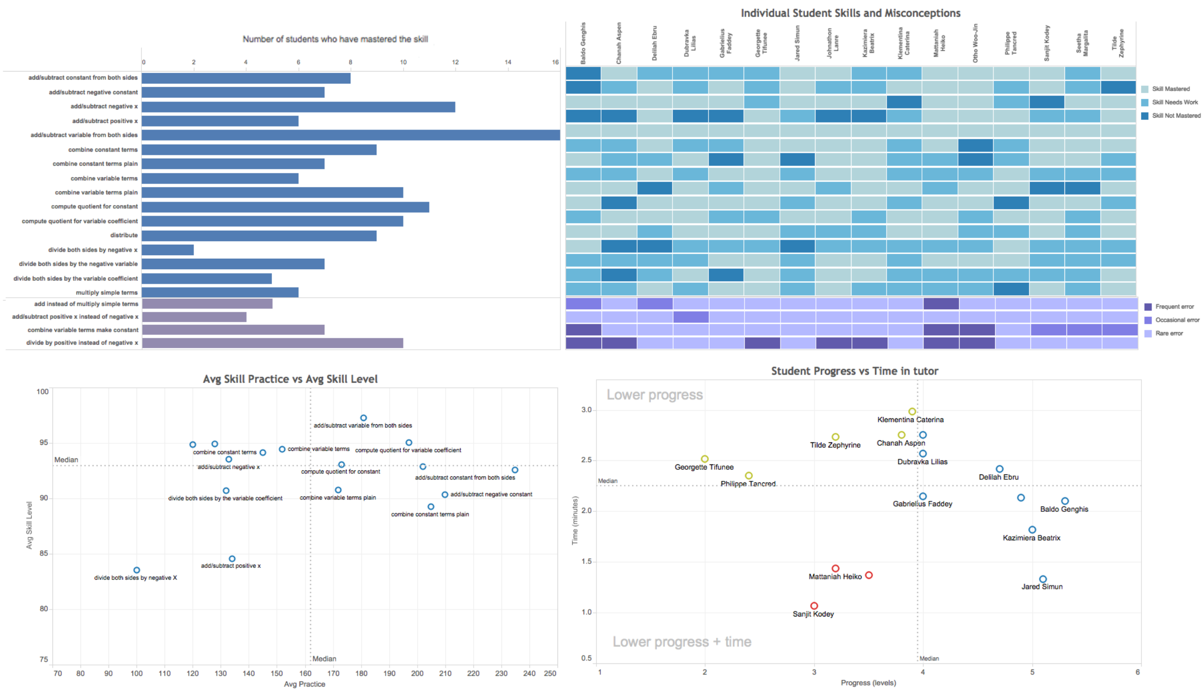


Figure 3. A medium-fidelity prototype created using Contextual Inquiry and Speed Dating data. It displays information (from top to bottom, left to right) on the number of students who have mastered each skill or have misconceptions, skill mastery and misconceptions per student, average skill mastery plotted against average amount of practice and student time in tutor plotted against student progress.

analytics they generate themselves. These analytics influence their decisions both at the class level and the individual level. We also found that teachers paid a great amount of attention to student errors, perhaps because (in a domain such as algebra) errors tend to be very actionable (e.g., the teacher might discuss the given error in class). The methods, data, and findings are described in more detail in [50].

3.2 Ideation And Speed Dating Through Storyboarding

Following Contextual Inquiry we generated broad design concepts and created storyboards that captured them in the form of illustrated stories addressing a central question (see Figure 2). These storyboards were then reviewed with teachers during Speed Dating sessions, high-paced sessions in which each teacher gave their quick impressions of each of the storyboards.

We conducted Speed Dating with 2 middle-school teachers from a suburban, medium-achieving school (2 male) and 1 female middle-school teacher from a suburban, medium-achieving school. We created 22 storyboards with focus questions that aimed to explore different types of data that the teacher might need in the dashboard but they currently do not have, such as wheel-spinning information (e.g., "Does information on students' wheel spinning in the tutor help guide your instruction?"). The questions also focused on whether the data should be shown at the class or the individual level (as shown in Figure 2), and how this data could help the teacher drive and differentiate instruction (e.g., "What notes and reminders from the dashboard help you make decisions as you prepare for the next class?"). Lastly, we wanted to test some futuristic ideas, in particular regarding the power separation between the teacher and the dashboard. From Speed Dating we found that teachers think it would be useful to see data and analytics provided by ITSs that teachers do not currently have, such as wheel-spinning information. In addition, we found that teachers like to have power over the dashboard and its decisions, and would not prefer having the dashboard have full control or power over the students.

3.3 Prototyping

Based on our findings from Contextual Inquiry and Speed Dating, we created an initial medium-fidelity prototype of the dashboard for use in the next-day scenario (shown in Figure 3). Recall that in this scenario, the teacher uses the dashboard "offline" (i.e., outside of class) to prepare for an upcoming class session.

We conducted prototyping sessions with this medium-fidelity prototype with three middle-school faculty (two teachers, one educational technology specialist), in which we showed them a paper print out of this prototype and asked them to pretend they were preparing for a next-day lecture, while also 'thinking aloud' as they walked through the interface. We also encouraged the participating teachers to ask the interviewer questions about any components of the dashboard interface that they did not understand, as well as to provide criticism and generate design alternatives (e.g., by drawing on the mockup). The interviewer also asked for elaborations throughout each prototyping session, based on the participants' questions and feedback. For example, two teachers requested that the dashboard generate high-level summaries (e.g., lists displaying the students, skills, and misconceptions that most require the teacher's attention) to help teachers reach actionable insights more quickly. In each case, however, further discussion suggested that these teachers would find it difficult to trust such summaries without being able to view

Figure 4. One of the two screens of high-fidelity prototype of the dashboard that was used in a classroom study with real student data from the teacher's current classes. This screen displays information about the performance of the class as a whole, in the form of number of students who have mastered each skill (top-left), average skill mastery plotted against average amount of practice (right), and prevalence of particular misconceptions (bottom-left).

the "raw data" upon which these summaries were based, or to better understand how these summaries were generated. We are currently in the process of analyzing data from these prototyping sessions, to inform future design iterations. We are also conducting additional Speed Dating sessions to inform the design of a dashboard used in the on-the-spot scenario. In our current Speed Dating sessions, we are exploring the potential usefulness of a broader range of analytics, while also exploring some of the interesting tensions and trade-offs that teachers highlighted during our previous speed dating and prototyping sessions.

3.4 Classroom Evaluation Study With Dashboard Mockup And Real Data

Finally, we conducted a classroom evaluation study to test out our initial design for a dashboard for the next day scenario. As mentioned, in this scenario, a teacher uses the dashboard to plan what to do the next day in class, or the next day that the class will be in the computer lab working with the tutoring software.

We iterated on the medium-fidelity design of the dashboard based on feedback from a design professor at our institution, and created a high-fidelity design of the dashboard (as shown in Figure 4). This high-fidelity design has separate screens for class and individual level information; both screens display information about students' skills and categories of errors. These design decisions were grounded in the data gathered during the Contextual Inquiry and Speed Dating sessions. In this study, we used the high-fidelity design of the dashboard mocked up with Tableau, a data visualization tool (http://www.tableau.com/). Using Tableau, we created a realistic-looking dashboard with very limited interactive capabilities (e.g., tooltips) but without hooking up the dashboard to the Tutorshop backend. We populated the dashboard with real data from the teacher's current classes and students, but did so through a combination of Python scripts, Excel use, and Tableau code.

Our goal for the study was to (1) understand how teachers use actionable analytics presented in a dashboard to drive their instruction and (2) explore whether students learn better when the teacher uses a dashboard to monitor their performance and adjust instruction. At the time of this writing, we have completed the data collection and are starting to analyze the data.

We conducted the classroom evaluation study with 5 teachers from two different suburban, medium-achieving schools in our area. The 2 teachers from the first school participated with 3 of their classes each, while the 3 teachers from the other school participated with 2, 4 and 5 of their classes respectively. Students were required to take a 20-minute pre-test followed by 1.5 periods work with Lynnette (1 period is 40 min) and a 20-minute mid-test. Each teacher was given 20 minutes to prepare for a full class period and their classes were assigned in counterbalanced fashion to the experimental or control condition. After the teacher conducted the lecture, students took a 20-minute post-test followed by a delayed post-test one week after the lecture.

The sole difference between the two conditions was whether or not the teacher had the dashboard available during their 20-minute class preparation session. In the experimental condition, teachers were shown two next-day dashboards, one with overall class-level information (as shown in Figure 4) and another one with individual-level information. We asked them to prepare for class using the two dashboards as they saw appropriate. In the control condition, teachers were not given any information on their students' performance and were asked to prepare as they normally would for the topic of Linear Equations in middle-school mathematics.

4. DISCUSSION AND CONCLUSION

Teacher dashboards are emerging as a key way in which learning analytics might have a positive influence on educational practice. Although by now many dashboards have been created, we know of few projects that have focused on creating a dashboard for ITSs. These systems produce rich interaction data. Many analytics derived from these data have been used in research (e.g., in the EDM community), but use in a teacher dashboard is less common. There are many interesting open questions regarding whether and how analytics used in ITS research might be useful for teachers and in what form they need to be presented to be easily understood and actionable. We explore this question through a user-centered design approach, combined with experimental classroom studies. We consider multiple usage scenarios, focused on supporting teacher decision-making and self-reflection in blended learning environments that use intelligent tutoring software. Another aspect of our project that is somewhat unusual in comparison to other dashboard projects is that we are creating a dashboard for use in schools, rather than for the college level.

A technical challenge of the current project is that we are implementing a dashboard for a general infrastructure for ITSs research and development: the CTAT/Tutorshop infrastructure. This means that, by and large, the dashboard we create will be general to all intelligent tutors created within this infrastructure. It may thus become a testbed for further research into teacher dashboards for blended courses that use intelligent tutoring software.

Our ongoing work focuses on the design for the "on-the-spot" usage scenario, in which the teacher uses the dashboard while the students (as a class) are working with the tutoring software. We are following the same approach as described above, soliciting teacher feedback on storyboards and increasingly sophisticated prototypes. We expect this design to be substantially different from that of the dashboard designed for the "next-day scenario." Identifying these differences may be a research contribution in itself. We are currently analyzing the feedback and results of the experimental study presented above. These results will inform a planned redesign of the dashboard for the next-day scenario.

In parallel, we are working to create the dashboard front-end and integrate it with the CTAT/Tutorshop infrastructure. We are using Ember.js as our framework for the front end. On the back end we are building on the existing Ruby on Rails CTAT/Tutorshop infrastructure and the MySQL database. Our aim in extending Tutorshop is to (a) support additional analytics we intend to display on the dashboard, (b) provide updates to the dashboard in real time, and (c) allow for relatively easy plug in of additional "detectors" (e.g. detectors of students' help-use behavior and affective states). The latter is one way in which a dashboard project can push an ITS architecture towards wider functionality and generality.

Finally, we are planning to evaluate both dashboards (for the next-day and on-the-spot scenarios) through experimental studies in real classroom environments. In these studies, we will test whether a teacher dashboard can lead to increased learning gains on students' work in an ITS, through teacher intervention informed by the dashboard. Thus far, very little research has attempted to evaluate learning gains attributable to teacher dashboards.

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