Increasing Academic Success in Undergraduate Engineering Education using Learning Analytics: A Design-Based Research Project

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This paper describes the first iteration of a design-based research project that developed an early warning system (EWS) for an undergraduate engineering mentoring program. Using near real-time data from a university's learning management system, we provided academic mentors with timely and targeted data on students' developing academic progress. Over two design phases, we developed an EWS and examined how mentors used the EWS in their support activities. Findings from this iteration of the project point to the importance of locating analytics-based interventions within and across multiple activity systems that link mentors' interactions with an EWS and their interventions with students.

Introduction

Colleges and universities are increasingly aggregating and analyzing once disparate sources of data, such as a student's admissions records, academic history, and use of campus information technologies, all under the rubric of "learning analytics" (Campbell, DeBlois, & Oblinger, 2007, Fritz, 2011; Goldstein & Katz, 2005). Learning analytics (LA) is a developing research area and a topic of increased conversation; yet, most studies are often limited to intriguing possibilities and frequently lack assessments for specific interventions paired with LA tools (Parry, 2011; Rampell, 2008). In this paper, we describe the first iteration of a design-based research project that developed an early warning system (EWS) for an undergraduate engineering mentoring program. The purpose of this iteration was to identify the necessary infrastructure for building an EWS and to understand the factors affecting how the EWS was used.

The EWS described in this paper represents an application of LA that is gaining popularity across colleges and universities—the near real-time aggregation and analysis of students' use of information technologies, such as Learning Management Systems (LMSs), for the purposes of identifying students in need of academic support (e.g., Beck & Davidson, 2001; Macfadyen & Dawson, 2010; Morris, Finnegan, and Wu, 2005). One of the many benefits of using LMS data is that these systems are used by a majority of instructors and students on most campuses in the United States (Dahlstrom, de Boor, Grunwald, & Vockley, 2011; Fritz, 2011). While there is increasing interest in using LMS and other related sources of near-real time data, little research exists about documenting the specific ways users make sense of data generated by these systems or how instructors and other interested parties can effectively intervene with students with the support of LA tools (Johnson, Smith, Willis, Levine, & Haywood, 2011).

The EWS developed for this project aggregated data from a LMS at one university and provided near real-time data from that system to academic mentors in a program called the STEM Academy. The STEM Academy is a holistic student development program aimed at increasing the academic success of students who have historically been underrepresented in science, technology, engineering, and mathematics (STEM) fields. Developing an EWS in collaboration with an effective support program, such as the STEM Academy, provided a unique opportunity to advance the field of LA by identifying how mentors in the STEM Academy used the EWS to intervene with students.

Below, we provide a broad overview of LA research focusing on prior LA projects that used data generated from LMSs. In general, LA tools using LMS data can characterized by whether they provide data directly to students or provide data to an intermediary who then interacts with students. We report our results in narrative form, providing a chronology of events that describes the development of our EWS and supports answering the following overarching research question: "How did mentors use the EWS to inform their support activities with students?" We conclude this paper by addressing future directions for LA research.

Theoretical framework

Overview of Learning Analytic Research

At its core, LA is about using data to inform decision-making, where the motivation to use data to support educational decision-making has been a topic of conversation for over 30 years (e.g., Means, Padilla, DeBarger, & Bakia, 2009). And while differences exist between LA and prior data-informed decision-making in schools (see van Berneveld, Arnold, & Campbell, 2012), many of these differences appear superficial for LA interventions that leverage data to identify students in need of academic support. Regardless of the label, research addressing how individuals use data to inform decision-making is influenced by multiple factors, such as the sources of data used and how they are presented; institutional, organizational, and individual factors affecting how one makes sense of data; and the various scaffolds that can impede or support an actor's sensemaking (Moss, 2007). Many of the past failures associated with data-informed decision-making in schools can be attributed to oversimplifying or ignoring any one of the above influences (Moss, 2007). One way LA researchers can avoid similar mistakes is to situate the use of LA tools within larger "activity systems" (e.g., Kaptelinin & Nardi, 2006). We base our use of activity systems in line with Cultural Historical Activity Theory (e.g., Engestrom, 1987), which delineates how actors, tools, goals, communities, rules, and divisions of labor mutually constitute outcomes associated with a mentor's use of the EWS and subsequent actions taken by students. We argue that thinking across activity systems provides a useful way to map the use of an LA tool with student outcomes.

LA researchers regularly highlight the need to overcome multiple technical challenges in the development of LA tools, such as aggregating and analyzing diverse sources of data. Many researchers identify these technical challenges and speculate on the power of LA through small-scale "proofs of concept" (e.g., Dawson, Heathcote, and Poole, 2010; Heathcote & Prakash, 2004; Romero, Ventura, & García, 2008). For researchers who have expanded beyond the proof of concept stage, two distinct LA research agendas are beginning to coalesce. One agenda involves aggregating data from online learning environments and providing these data directly to students; another direction involves taking similar sources of data and providing them to an intermediary, such as a course instructor or academic advisor, who then acts on that data with and for students.

An example of a system that provides data directly to students is the Context-aware Activity Notification System (CANS). Within a distance education context, Goggins, Galyen, and Laffey (2010) found that students were able to use feedback provided by CANS to identify what their peers were doing, and what they, in turn, might need to do in order to catch up to their peers. LA interventions that provide data directly to students often have a more direct link to positively affecting student learning. Intelligent tutoring systems, for example, provide students, real-time direct scaffolding as they work to solve geometry problems. Tools, such as, E^2Coach at the University of Michigan, provide tailored messages to students based on demographic and course performance data (McKay, Miller, & Tritz, 2012). These messages are meant to motivate students to take specific actions, such as allocating more time to prepare for exams. For direct-to-student LA tools, what and how data is presented to students appear to be important areas of research that are just getting under way.

Work by Dawson, McWilliam, and Tan (2008), is an example of an LA tool that provides data to an intermediary—an instructor. They observed that when an instructor had data on students' use of an LMS it allowed the instructor to identify students in need of support. Purdue University's Signals project is another example of an LA tool that provides data to instructors as well as to students. This tool analyzes three sources of data: student demographic data, student grades, and students' use of the LMS (Campbell, DeBlois, & Oblinger, 2007). These three data sources are formulated into a prediction model that assesses the likelihood of a student's academic failure. Instructors have the added ability to send messages to students based on a student's classification.

Across both direct-to-student and direct-to-intermediary LA tools, the user directly interacting with the tool is engaged in some form of sensemaking that supports a subsequent action. Some of these subsequent actions are more complex than others and the ways in which the LA tool scaffolds this sensemaking can have an effect on these subsequent actions. For direct-to-student tools, students' sensemaking may be related to subsequent actions, such as attempting a new problem solving strategy within an Intelligent Tutoring System or availing themselves of more study time based on recommendations made by E^2Coach or Signals. For direct-to-intermediary tools, such as the one developed in this project, the intermediary is doing the sensemaking and making recommendations to students. The student then interprets the recommendation made by the intermediary. This added step, or activity system, has both affordances and constraints. The affordance of this approach is that a human is doing the recommending and drawing on sources of data, such as prior interactions with the student, that are not collected by a computer system. A constraint of this approach, however, involves scalability. A direct-to-student system can have infinite patience in collecting data and making recommendations, and it can also provide consistency in feedback that does not fall victim to human biases. Lack of consistency is another constraint, specifically from a research perspective, because a human making a recommendation can make moment-to-moment modifications in what gets recommended to a student. This moment-to-moment variation may not be amenable to measurement in consistent ways or justifiable within formal decision frameworks in the same way that automatic recommender systems can.

LA Tools and Activity Systems

An important theoretical hurdle for LA tools that provide data to an intermediary is connecting an intermediary's use of an LA tool to changes in a student's outcomes. Generally speaking, there are multiple steps in the process, and breakdowns at any point can affect the likelihood of a student obtaining positive academic outcomes. We outline four activity systems that, combined, may be thought to lead to desired student performances. Our starting point involves an actor, in our case a STEM Academy mentor, receiving data on a student or students of interest. An initial goal of the mentor is to identify students in need of support. While this may be an initial goal, one's goals can shift through interacting with the EWS. The mentor, for example, may go from identifying specific students to explaining a specific student's source of failure. Based on how a mentor makes sense of student data, the mentor may then contact a student to come in for a meeting to discuss that student's progress. From this meeting, a mentor may recommend a specific course of action for that student, on which a student may or may not act. Depending upon what occurs following that recommendation, a student might perform better than expected on a subsequent course assessment.

There are four general and interrelated activity systems related to the above description: (1) A mentor receives a data display and examines students' performances. The outcome of this engagement is some form of communication with a student, which leads to another activity system (2) where mentors engage students and a recommendation is made If a student acts on the recommendation, then he or she engages in another activity system, (3) such as a study group, whereby the outcomes may include some increased knowledge. And lastly, (4) a student engages a subsequent course assessment with new insights gained from activity system #3, and a plausible outcome is a better than expected score on this assessment.

The above collection of activity systems points to several complex interactions, any one which may not lead to intended results but all of which represent the steps necessary to affect student learning—stemming from a mentor's interaction with an EWS. The iteration of this project described in this paper addressed the first of these activity systems. We developed the EWS to influence how a mentor identifies students in need of academic support with the intent of increasing the frequency with which a mentor contacts students and engages with them in discussions around their academic performances. We view the efficacy of our overall intervention related to the enactment of these systems. Variation in these systems, we speculate, affects our intended outcome—students' academic success. We operationalize academic success as students' final course grade and persistence in STEM fields, but have not yet linked our intervention to specific student outcomes. Instead, the current iteration assessed how mentors engaged students differently and to different degrees as a result of having access to the EWS.

Data and Methods

Our research agenda is organized around principles of design-based research (Brown, 1992; Collins, 1992; Collins, Joseph, & Bielaczyc, 2004). Design-based research involves “a series of approaches, with the intent of producing new theories, artifacts, and practices that account for and potentially impact learning and teaching in naturalistic settings” (Barab & Squire, 2004, p. 2). A distinguishing feature of design-based research is that the development of tools and theories is a collaborative effort among researchers and participants (Cobb, Confrey, diSessa, Lehrer, & Schauble, 2003). In our work, we were focused on identifying the possible ways in which the EWS functioned in and across various activity systems and the factors affecting how mentors used the EWS.

Description of the Intervention

The intervention developed for this project utilized aggregated data from a learning management system (LMS) at one university and provided near real-time data from that system to mentors in an undergraduate engineering retention program, the STEM Academy. To support students’ academic success, the EWS was developed to shorten the time frame from when academic mentors first become aware of a student in need of support and their intervention with that student. In the first two years of the STEM Academy, 2008-2010, mentors relied on students’ self-reported grades that students brought to monthly meetings. On this monthly time scale, once a student had failed an exam it was often too late to correct a student’s academic trajectory.

One solution offered in fall 2010 was to provide mentors with data on students’ performances from the campus LMS. The LMS tracks interactions between and a user and the system in the form of “events” and “tables”. Events can include anything from the number of times a student accesses a course site to when a student downloads a specific course reading; tables are structured data, such as a course site’s Gradebook (GB). Using data from different events and tables as well as various technological tools (e.g., R, Microsoft Excel, and database and web-authoring tools) we engaged in an iterative, collaborative design-based approach to develop an EWS for the STEM Academy mentors. In line with design-based research, we sought to better understand how various activity systems aligned to promote students’ academic success. We speculate that these activity systems span a mentor interacting with the EWS to a student engaging a later course assessment. For this iteration of the overall intervention, we collected data related to how mentors interacted with the EWS and how these interactions changed the degree to which mentors contacted STEM Academy students.

Description of the EWS Data

Data used by the EWS are drawn primarily from the university’s LMS. Specifically, the LMS’s Gradebook and Assignments tools were used to follow students' grades over the course of the term. We also tracked the number of times a student logged onto a course's LMS website to help contextualize students’ grades. Grades and log-in events were aggregated and translated into a variety of visualizations, including figures displaying students’ grades compared to their peers over time along with lists of performances on individual gradebook entries. This information was updated and sent to mentors on a weekly basis. We developed a three-level classification scheme of Engage (red), Explore (yellow), and Encourage (green) that provided mentors with a simple depiction of the complex relationships between academic performance data, including longitudinal data and intra-course comparisons, and log-in events.

Methods

Design iterations occurred in two phases, corresponding with two academic semesters. Along with clarifying how LMS data could be integrated into visual displays and classification schemes, we also engaged in a variety of data mining activities between the two academic semesters. The purpose of this data mining activities was to identify patterns between a student's use of the LMS and his or her final course grade. We used functional data analysis techniques (Ramsay, Hooker, & Graves, 2009) to explore relationships between students' use of both the LMS in general and specific LMS tools with their final course grades across multiple engineering courses. Using the 16 weeks of an academic semester, we estimated a smoothing spline across weeks and explored the relationships between course site log-ins and a student's course grade. This process allowed us to create smooth plots of LMS use over time for both the course as a whole as well as for groups of students who earned the same final grades. We were also able to take the first derivative of each of these plots that yielded information about the week-to-week changes in course site log-ins and tool use.

To capture how the EWS was used across activity systems, we conducted multiple individual and group interview sessions with mentors. We conducted three interview sessions with STEM mentors where they participated in group-discussions and think-aloud exercises to reveal how they interacted with the EWS. Along with these interview sessions, we conducted weekly meetings with STEM Academy mentors and faculty members. These weekly meetings served as regular points of contact and provided opportunities for mentors to describe how they were using the EWS. During these weekly meetings, we also discussed design issues, such as what data were useful to mentors and why. For example, we would describe possible sources of data and get their feedback on how they would use these data before and after their mentoring activities with students. Below, we report our results chronologically, specifying the development of the EWS and the ways in which the EWS was appropriated within and supported the enactment of subsequent activity systems.

Development and Use of the EWS

Phase I

EWS Design

In fall 2010 we began working with the STEM Academy to develop an EWS. During this phase, we conducted a needs assessment to determine what information would be most useful for mentors to support their mentoring activities. The basic need involved providing up-to-date grade information to mentors on students enrolled in the STEM Academy. We provided an initial solution to this problem by querying the campus LMS for all course sites that included a STEM Academy student and that used the GB or Assignments tool. Course sites without GB or Assignments tools would not allow us to track students' developing grades. Our hope was that there would be multiple courses where an STEM Academy student was enrolled and that had an active GB. We located large numbers of courses that enrolled a STEM Academy student, such as required courses in engineering; yet other important courses, such as introductory mathematics, did not use either the GB or Assignments tool and thus could not be tracked using the LMS. Despite this fact, In Phase I we tracked over 150 students across 400 courses and in Phase II, we tracked over 200 students across 600 courses.

An additional constraint in working with these data involved the validity of the information provided in the GB and Assignments tools. The validity of these data were dependent upon how instructors actually used the GB and, more generally, how instructors used the LMS website as part of their instruction. Instructors' idiosyncratic uses for the GB were related to how they structured their grading systems. For some instructors, each gradebook entry contributed to a final course grade based on the total points possible for an entry while other instructors applied specific weights to each gradebook entry, regardless of points possible, to determine the contribution of an individual assignment to a final course grade. In addition to weighting, another aspect of instructors' idiosyncratic use was related to the actual gradebook entries they posted to the GB or Assignments tools. For example, some instructors only posted homework assignments to the GB and did not post, for example, grades that contributed substantially to the final course grade, such as exams. Thus, based on instructors' idiosyncratic use of the GB and Assignments tools, we reported a non-grade equivalent percent of points earned out of points possible to academic mentors.

In February 2011, after aggregating GB and Assignments data collected from the LMS, we created a multiple sheet, Microsoft Excel file for mentors. First, we designed a "Mentor Summary" sheet that allowed mentors to view all STEM Academy students' percent of points earned out of points possible for each course in which an STEM Academy student was enrolled. Along with the summary sheet, we created individual sheets for each student-course combination. These individual sheets provided longitudinal depictions of a student's developing course grade. To help mentors parse the large amount of data, we developed a classification scheme that highlighted students who may be in need of academic support. By highlighting those students in the greatest need of support, we specified actions that a mentor could take in relation to that student: Encourage (green), Explore (yellow), and Engage (red). To determine the specific decision rules associated with the classifications of encourage, explore, and engage, we worked closely with STEM Academy mentors. Classifications were initially generated using two rules:

(1) whether a student's percent of points earned was at or above the thresholds of 85%, 75%, or 65% and (2) whether a student was 10% (low end of non-grade equivalent distribution) or 15% (high end) below the course average on percent of points earned. We further clarified the fine-grained structure of the classification scheme through two additional collaboration sessions with all mentors and two subsequent interviews with one of the mentors.

Between the use of a non-grade equivalent and our classification scheme, we recognized that by using solely GB information, the EWS was over-sensitive in classifying students as Explore (yellow) and Engage (red). The EWS was particularly over-sensitive in the early weeks of a semester when there were few grade entries available. Mentors, however, expressed benefits from over classifying students as Explore (yellow) or Engage (red) based only on a few early course assignments in that it provided them with opportunities to hear students describe their course performances. Classifying these students in such a way provided the opportunity for mentors to identify and provide support to all of these individuals *before* they took their first exam or submitted an assignment that contributed substantially to their final grade. Even though the EWS classified more students than were actually performing poorly in some courses, no additional harm came to misclassified students because later in the semester, issues with the classification scheme being over-sensitive were attenuated after more points accrued. This was especially true for those courses in which assignments were inherently weighted.

While grade information was useful to advisors, we also explored other sources of data from the LMS to help mentors contextualize a student’s course grade. For example, we examined correlations between the degree to which students used specific LMS tools, such as Chat and Discussion, and their final course grades. Our initial thinking was that providing information about tools that are predictive of final course grades would be beneficial to mentors. We used functional data analysis to plot changes in students' use of the LMS in line with their overall course grade. However we found little evidence that frequently utilized course tools were related to course grades. The general strategy of seeking correlations between a tool's use and a final course grade is related to a familiar strategy in LA research—developing prediction models to assess the likelihood of academic failure.

Our research efforts surfaced multiple limitations with developing prediction models to assess students' likelihood of academic success. Unlike some systems, such as Intelligent Tutoring Systems that guide and assess student progress through a well-defined problem space, LMSs and a variety of other online learning technologies are necessarily designed to be content agnostic and dependent on how an instructor integrates them into course-specific activities. Given this reality, patterns in LMS use are often not generalizable across multiple course sites. Stated more succinctly, the way an instructor integrates the LMS into his or her course site is explicitly linked to the validity of the data. For example, if the course site is not an important part of course activities, data from how individual tools are used on these course sites may lead to spurious conclusions related to a student's academic progress. After analyzing patterns across multiple tools and course sites, and given the threats to validity related to generalizing across course sites, we began relying less on sources of data that would be "predictive" and instead worked with sources of data that mentors would find useful in understanding a student's course performance.

How Mentors Used the EWS

Mentors described their use of the EWS during this iteration as "sporadic." Interestingly, early collaboration sessions where we provided mentors mock-ups of EWS designs proved most beneficial to mentors. After looking at the initial displays, drawn from actual student data, mentors were able to identify students who needed immediate help. Mentors contacted these students and worked with them to identify improvement strategies. One reason mentors gave for not using the EWS more regularly during this phase is that they had not yet found a way to integrate it into their regular work practices. Another reason for not viewing the EWS frequently is that first-year STEM students met with mentors on a monthly basis and turned in progress reports on their courses at this time. Mentors have used these sheets for multiple years and these sheets had become integrated into their regular mentoring work.

Contrary to their experience with first year students, Academy mentors reported that the EWS was useful in tracking the performance of students in their second or third years that were no longer required to attend monthly mentoring sessions. While not an initial goal of the EWS, tracking these students was useful because they were often "under the radar" until final course grades were made available to mentors. Despite collaboration around the design of the interface, mentors also reported that the overall EWS was not user friendly, with the exception of the red, yellow, and green color-coding. These colors helped mentors quickly make sense of the large amounts of data they received.

Based on the structure of this iteration, the EWS had both intended and unintended effects related to the activity system on which we were most directly intervening. The activity system involved a mentor interacting with the EWS and was affected by the design of the tool. Initially, the tool was not useful for tracking first-year STEM Academy students. It was, however, useful for identifying students who were past their first year in the Academy. These students, based on mentors' use of the EWS, were contacted more frequently than in past semesters. This increased contact led to more meetings between a mentor and a student, and more opportunities for students to avail themselves of academic support services. In the next phase of design, we worked with mentors to improve the usability of the EWS and identify ways in which using the EWS led to increased contact with all students.

Phase II

EWS Design

In fall 2011, we released a new version of the EWS to mentors. Based upon mentor feedback from the winter semester, we included names for individual assignments on each of the student report sheets. While the Engage, Explore, and Encourage classification scheme alerted mentors to those individuals in need of their intervention, it was based on relative, intra-course grade measures. As we previously stated, these measures did not distinguish between the importance of gradebook entries, potentially biasing classifications. Including the individual gradebook entries helped mentors in making sense of a student's classification within each course. We also incorporated the number the times a student accessed a course site into the classification scheme. We used a combination week-to-week and cumulative access events to classify students on the borderline of specific grade thresholds. For example, if a student averaged below the 25th percentile for log-in events and was on the borderline between a B and B-, the student would be classified as Explore instead of as Encourage.

How Mentors Used the EWS

Based on these different design modifications as well as and a regular, weekly distribution of the EWS, mentors used the EWS in this phase more frequently. Due to this increased use, mentors found that the EWS supported their mentoring activities more in this phase than in the first phase. After a few weeks of regular use, mentors asked for additional data to support their work. One mentor asked researchers to aggregate and display students' first exam scores for one core engineering course outside of our regular, weekly distributions of the data. Mentors found from previous semesters that the first test in this course was important to a student's final grade. Using this exam data, the mentor identified students who did not do well and organized a post-exam session where a graduate student was available to help the students identify what they could do to better perform on the next test.

Mentors found the new design feature of listing individual gradebook entries underlying a student's overall performance useful for focusing their interactions with students. Having scores for individual gradebook entries allowed mentors to address specific areas of concern within a course. For example, one mentor specifically targeted students' performances on major exams to help students make decisions about dropping courses and the degree to which a student needed to work with the course instructor on improving his or her grade.

We were also able to identify tentative links between the ways in which mentors used the EWS and the frequency with which mentors contacted students. In this phase, mentors reported contacting all students classified as Engage on a weekly basis. Mentors typically emailed students to schedule a meeting where specific improvement strategies were discussed. Most mentors received immediate responses from all first-year STEM Academy students and from approximately half of all STEM Academy students who had been in the program longer than one year. Strategies for improvement included setting up appointments with tutoring services, meeting with a course instructor, attending office hours, and reading through the instructor's posted PowerPoint slides before and after lecture. Thus, the EWS provided a view of student performance that signaled to mentors which students they might want to contact.

To illustrate specifically how the EWS was used, we describe how one mentor used the EWS. (1) The mentor filtered the sheet to identify his students and (2) would then locate all students who were classified as Engage (red) and viewed each student's individual grade sheet. (3) After selecting an individual student's sheet, the mentor would then examine how the student performed on each grade entry. (4) After examining individual entries, the mentor would examine a longitudinal graph of the student's course grade. (5) The mentor would then email the student requesting a meeting to discuss his or her academic performance. Though individual mentors varied in their processes by which they used the EWS and contacted students, in general, mentors stated that they used multiple sources of additional information in conjunction with the data presented in the EWS. For example, prior history with each student and the mentor's own knowledge about specific courses and instructors impacted what they would say in both their initial communications and one-on-one meetings with that student.

One way that we assessed the benefit of mentors' use of the EWS was to examine the number of first-year students who were contacted between their regularly scheduled monthly meetings. There were three sets of weeks where students did not have their regularly scheduled meeting, and therefore did not have required contact with mentors. If a student was classified Engage in any of these intervening weeks, we counted that student as having been contacted based on the feedback the mentors gave during interviews. In the first intervening week, 2 first year STEM Academy students and 25 second-fourth year students were classified as Engage. In the second and third intervening weeks, 3 and 7 first year students and 23 and 27 second-fourth year students were contacted, respectively. These measures demonstrate an overall increase in contacting students due to mentors' use of the EWS.

Conclusion

This paper reported on the first iteration of a multi-year project aimed at developing an EWS for an undergraduate engineering mentoring program. The mentoring program served as a strategic research partner providing us with an authentic context in which to explore important issues related to LA-based interventions, while simultaneously providing a working product that supported Academy mentors identify students in need of academic support. To understand the relationships between EWS-use and students' academic successes, we identified important theoretical implications related to LA research, namely, the complex interplay of multiple activity systems. We speculated that for LA-based interventions aimed at providing data to an intermediary, such as a course instructor or academic advisor, there are multiple systems necessary for supporting a student's subsequent course performances. We outlined four such systems, and collected data on the first: (1) mentors interacting with the EWS, (2) mentors engaging students and making a recommendation, (3) students engaging in some practice related to the recommendation, and (4) students participating in a course assessment with knowledge, skills, and dispositions gained in activity system #3. These activity systems are perhaps unique to the use of the EWS for this project; however, when an intermediary's use of an LA tool and a student's participation in a subsequent course assessment is the focus of research, we argue, multiple activity systems will be formed.

By understanding how mentors interacted with the EWS (activity system #1), we found that giving mentors access to data on student performances influenced the degree to which they intervened with students. We recognize that this is only one step in the process of having students take actionable steps based on that information. In future work, we will continue to partner with the STEM Academy to draw clearer links between the activity systems that we believe influence student outcomes. While collaboration with mentors was critical to the development of the EWS, in line with design-based research, we cannot discount the important role that we as researchers played in this intervention. For example, we helped mentors identify data that would be useful to them and ran individualized queries when they needed additional data on students. Future LA research will benefit not only from identifying the ways in which LA tools cross multiple activity systems but also from identifying the ways in which tool developers, researchers, and data scientists support actors make sense of and act on data used in LA-based interventions.

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