It's My Data! Tensions Among Stakeholders of a Learning Analytics Dashboard

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ABSTRACT

Early warning dashboards in higher education analyze student data to enable early identification of underperforming students, allowing timely interventions by faculty and staff. To understand perceptions regarding the ethics and impact of such learning analytics applications, we conducted a multi-stakeholder analysis of an early-warning dashboard deployed at the University of Michigan through semi-structured interviews with the system's developers, academic advisors (the primary users), and students. We identify multiple tensions among and within the stakeholder groups, especially with regard to awareness, understanding, access and use of the system. Furthermore, ambiguity in data provenance and data quality result in differing levels of reliance and concerns about the system among academic advisors and students. While students see the system's benefits, they argue for more involvement, control, and informed consent regarding the use of student data. We discuss our findings' implications for the ethical design and deployment of learning analytics applications in higher education.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Education**.

KEYWORDS

Learning analytics; early warning dashboards; higher education; student data; privacy; ethics.

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1 INTRODUCTION

Learning analytics systems use and analyze learners' behavioral and interaction data to understand and optimize learning experiences [56]. Learning analytics applications have been deployed in educational institutions for various purposes, including teaching systems for instructors [32], learning platforms for students [61], and student performance tracking tools for academic advisors [19]. So called early warning systems or dashboards analyze education data to identify underperforming students [10] and enable timely interventions by instructors or academic advisors [40].

As learning analytics, particularly early warning systems, become a more integrated part of the higher education experience, many issues and challenges arise, including ethical and transparent use of student data [26], student data privacy concerns and rights [14, 41], considerations of informed consent [21], data access control [47], and responsible interpretation of student data [23]. Addressing these issues is important in order to promote trust in learning analytics systems [16, 53], improve quality and effective learning and teaching [57], and increase the acceptance of learning analytics among stakeholders [41].

To understand different stakeholders' perceptions, attitudes, and expectations towards the access, use and analysis of learners' data through learning analytics systems, we conducted 32 semi-structured interviews with three groups of stakeholders (4 developers, 8 academic advisors, and 20 students) of an early warning dashboard, called Student Explorer (SE) [36], deployed at the University of Michigan. SE uses student data periodically aggregated from learning management systems to analyze student performance, enable academic advisors to check students' academic progress, and help advisors identify students who may need academic support [32].

Our multi-stakeholder analysis revealed tensions among and within stakeholders with respect to this learning analytics system. Our key findings fall into four categories: **(1) Context of Usage**: How the system was designed to function and how it currently operates differ. SE's usage has evolved, meaning that who has access to SE and who maintains SE have changed substantially. **(2) Perceptions of Stakeholders' SE Access**: Stakeholders hold different views on who should be able to access SE and its student data, and for which purposes. This is coupled with a general unawareness by stakeholders of who currently can access SE. **(3) Data Validity**: Due to changes in use, SE's interface does not adequately convey potential issues and limitations with the underlying data or its presentation in SE. **(4) Student Consent and Involvement**: Students were largely unaware of SE's existence. While they recognized the benefits of SE, they advocated for informed consent and more involvement and control in how educational data about them is used.

Our findings highlight the need for better engagement of all stakeholders, both, in the design and development of learning analytics systems, but also once they are deployed. Furthermore, the origins and quality of data used should be communicated clearly in a learning analytics system's interface, rather than relying on out-of-band cultivation of institutional knowledge. Finally, we discuss how learning analytics systems could be designed to better consider students' privacy concerns and desire for involvement and control about their data, as well as their education.

2 BACKGROUND AND RELATED WORK

Higher education institutions are increasingly making use of learning analytics to support student learning [3, 64]. One of the most common data sources for learning analytics in higher education are Learning Management Systems (LMS), which are platforms used for course content delivery, assignments, and other course-related activities [35]. LMS typically log detailed information about student access (e.g. login times, frequency of accessing course materials) [29]. Universities are using data generated by LMS and other tools to better understand learning processes [52], develop improved and new curricula [11], and increase student success [1]. One prominent use of learning analytics that draws data from LMS is the assessment and prediction of students' academic performance [7]. For instance, Early Warning Systems (EWS) leverage predictive models to identify students who are at risk of underperforming academically early on, allowing for timely interventions by instructors or academic advisors [10, 37], as well as self-reflection by students [6].

Such EWS typically collect and process vast amounts of student data, including grades, attendance, honors and awards received, graduation plans, and when online assignments or activities are accessed by students [3, 20, 44]. The data collection, aggregation, storage, and processing raise questions and concerns regarding privacy, control, access [41, 44], and adequacy of algorithmic analysis [26]. For instance, to what extent students should be informed or consulted on the use of student data, and whether they should be able to opt out [57, 58]. Concerns regarding data usage touch on whether student data provides a sufficiently complete representation of learning [18]; the importance of fair interpretation of data [63]; the appropriateness of using data to inform educational practices [54] and its impact on the education goals [8]; whether "immature use of data" could dissatisfy people's expectations for personalized learning [12]; and to what extent current learning analytics algorithms can provide an accurate assessment of learners [15, 50].

This echoes broader concerns of bias and discrimination in algorithmic decision making [27]. Algorithms may suffer from different inherent biases, such as pre-existing bias from social institution and attitudes, technical bias due to technological constraints, and emergent bias resulting from a system's context of use [24]. "Algorithms are mirrors" as models are created by and trained on data about humans [5], thus potentially replicating and exacerbating pre-existing biases in the data. The quality of algorithmic outcomes is inherently limited by how data is captured [38, 49]; difficult to encode factors are often neglected, such as cultural experiences, social connections, social norms, and other external factors [42]. At the same time, machine learning models and reasoning steps may be opaque and difficult to understand by humans, raising questions of algorithmic accountability and transparency [60] when leveraging machine learning models in decision making [26]. In the learning analytics setting, this poses the risk of making decisions based on an incomplete or inaccurate representation of students' learning experiences [26, 62].

To address these concerns in learning analytics, Drachsler et al. encourage involving learners and other stakeholders in data collection processes affecting them, in order to aid reflection on the appropriate use of student data and facilitate trust between stakeholders and the institution [16]. Others advocate for more transparency about learning analytics, e.g., clearly informing stakeholders what data is being collected, with whom it is shared, and how it is being used [9, 47]; or taking a corrective perspective toward the reliability of algorithmic decisions [4, 5]. Explicit policies should govern and guide fair data use [45], including appropriate interpretation of data [26, 44], involving instructors in addition to students in design and usage of early warning systems [7], granting students access to their data [46], and anonymizing student data so as to ensure student privacy [15].

While prior work has evaluated the deployment of learning analytics systems at various institutions, and how relevant stakeholders perceive the effectiveness of such systems, few have done so from an ethics or privacy perspective. Nottingham Trent University has taken a transparent partnership approach to communicate, test and implement a learning analytics dashboard, after ethics concerns were raised by staff members [55]. A survey on students' privacy perception toward learning analytics revealed that students are conservative about sharing their online behavior data (e.g., login data, download frequencies) with the learning analytics systems [30].

Other studies have focused on the effects learning analytics systems have on students. For example, with student-facing learning analytics dashboards extra care needs to be taken in presenting information based on login frequency and duration, given that students might be sensitive to how they are being evaluated, and might manipulate their login data to influence their perceived performance in the system [43]. With proper implementation of feedback functions in a learning analytics dashboard, students are more likely to accept and act on feedback, rather than focusing on grade data [25]. In a study on Purdue University's Course Signals (an early intervention system), some students reported feeling demoralized by the system's warning messages [1]. Further, Lonn et al. found students' mastery of course material decreases when they are shown student performance data in relation to their peers, demonstrating a need to balance students' learning motivation and goals when designing learning analytics tools [34].

Despite the concerns and prior research regarding student data use in learning analytics, little is known about how these issues manifest and are addressed in deployments of learning analytics systems; and in particular what concerns different stakeholders have when confronted with early warning systems in practice. Our study on different stakeholders' perceptions and concerns with respect to a specific deployed learning analytics system, contributes insights on tensions among stakeholders' attitudes that may go unnoticed when focusing on individual stakeholders. Our findings highlight the need for involving different stakeholders not only in the design and development of learning analytics, but also throughout their deployment.

3 STUDENT EXPLORER

We focused our multi-stakeholder assessment on the deployment of a specific early warning system, Student Explorer (SE) [32, 36], developed and deployed at the University of Michigan. SE's main purpose is assisting academic advisors in identifying students at risk of academic jeopardy and facilitating outreach and interventions to those students [36]. At the University of Michigan, academic advisors are professional staffs associated with a given school's, college's, or department's undergraduate program. Through individual advising sessions, academic advisors help students with decisions and planning regarding their education, extracurricular opportunities, professional goals, and well-being. SE analyzes student data, such as students' assignment scores and login activities, from Canvas, the learning management system used at this institution. SE indicates whether a specific student is performing below, on par, or above the class average, and tracks a student's performance over time for a given class. SE is available to some academic advisors and administrators, students do not have direct access to SE.

Dashboard and Model

Student Explorer provides academic advisors with three different views on student performance (see Figure 1). The *student roster view* displays a list of students assigned to the advisor. A student's performance for each class they are currently enrolled in is summarized by icons. The icons indicate whether the student is performing above (green checkmark), on par (yellow triangle) or below (red exclamation point) class average. Classes without LMS data available are marked with a gray dot. The *course summary view* shows a specific student's performance (blue) in comparison to the class average (yellow) for all courses. The *individual course view* shows a student's weekly cumulative performance in a course over the semester (blue) compared to the course average (yellow), as well as the student's aggregated course page engagement as measured by the LMS site page views or log-ins. Daily assignment scores and weekly student login activity are updated automatically based on LMS data [34].

SE uses a fixed classification scheme consisting of nine rules that take into account a student's (1) percentage of grade points earned, (2) grade difference from the class average, and (3) LMS course site page view percentile ranking to classify student performance into three colored categories [36]. The main criterion is student percentage of grade points, which is divided into five segments (below 55%, 55% to 64%, 65% to 74%, 75% to 84%, and above 85%) [31]. Students who have earned more than 85% of the grade points are marked green; students below 55% are marked red. For students with scores in the middle three segments, their classification (red, yellow, green) is based on a set of rules which are dependent on the difference from the class grade average and course site page view percentile ranking. For example, a student with grade points between 75% to 84% would be marked as green if their grade is fewer than 15 points below the course average, or if their course site page views ranks in or above the 25th percentile; if lower, the student is marked as yellow [31].

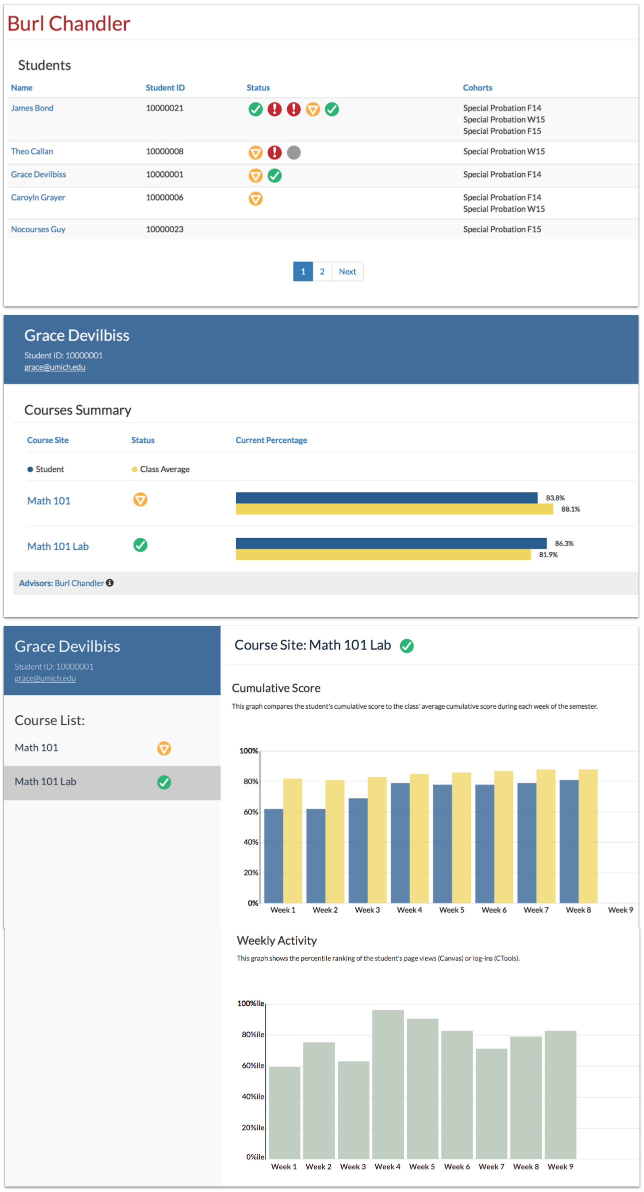

Figure 1: Student Explorer's interface: student roster view (*top*), course summary view (*middle*), and individual course view (*bottom*).

Deployment and Stakeholders

SE was first deployed in 2011 for advisors helping underrepresented students in STEM disciplines. With proven positive impact on students' overall grade point average (GPA) [32], SE was refined further and promoted more broadly in 2013 to 26 academic advisors, touching 650 undergraduate students [36]. During the 2017-2018 academic year, SE has been used by over 100 academic advisors from multiple schools and colleges across the university. The model, as described above, has remained unchanged since 2013.

SE has three key stakeholders, on whom we focused in our study. *Academic advisors* are the primary users of SE as they incorporate it to their advising activities with individual students. *Students* are affected by SE because SE uses data about them and may impact their academic advisor's behavior. The third stakeholder group are SE's *developers*, who built the operational version of the system now in deployment.

Student Explorer has additional stakeholders, who we did not study due to their only indirect role in SE's use and operation: The researchers who developed and validated SE are no longer involved in SE's operation; course instructors who manage their courses through the LMS can affect the data reflected in SE, but have no access or exposure to SE; and the IT personnel responsible for SE's operation and maintenance.

4 STUDY DESIGN

We conducted a multi-stakeholder analysis of SE's deployment to understand key stakeholders' respective perceptions and concerns through in-person, semi-structured interviews with developers who built the deployed version of SE, academic advisors who use SE, and undergraduate students, whose data is used by SE. Our study was determined to be exempt from oversight by our institution's IRB.

Interview Protocols

We developed interview protocols for each stakeholder group, which included the same or similar questions in many regards but were tailored to the specific stakeholder. The final interview protocols are available as supplemental material.

We started with developers' role and experiences in the design, development or operation of Student Explorer. Then we asked them to describe how SE works and why it was created. Following a walk-through of SE's interface, we incorporated questions about SE's features and functions, users, data processing, and user feedback. Next, we asked in more detail about the data in SE, including data reliability, data protection, data accuracy, and, both, benefits and issues of using student data. Next, we asked developers about students' awareness, access and participation regarding SE, as well as SE's impact on students and the learning environment. This was followed by questions about SE's potential benefits and concerns. If developers did not mention it themselves, we asked whether they saw any ethical and privacy issues with SE. We concluded the interviews after asking about future SE improvements.

The advisors' interview protocol was similar, with a few exceptions. In the beginning, we asked advisors to describe a typical advising session with a student. We then asked if they were aware of SE, how they used SE either in preparation for or during advising sessions, and their basic SE usage pattern (frequency, duration, training etc.). Next, we showed them SE screenshots and asked them to describe their impressions and experiences of SE's interface (symbols, graphs and texts), functions, and data sources in order to understand to what extend their mental models of the system aligned with its actual operation. We further asked them about benefits, concerns, issues and impacts regarding SE.

We began student interviews by asking about their academic advising experiences. We then asked about SE. If the student was unaware of SE, we introduced SE by showing screenshots of SE's three views. We asked their opinions on SE's interface, purpose, functions, and how the data in SE might be generated. We then asked what they saw as SE's benefits or issues. We concluded with specific questions on student access, consent, and student options regarding SE's use of student data, if they had not been brought up organically by the student.

Participant Recruitment and Demographics

Between October 2017 and February 2018 we interviewed 4 SE developers, 8 academic advisors from different units, and 20 students majoring in a range of subjects at the University of Michigan. Student participants were compensated $10; advisors and developers participated during work hours and did not receive additional compensation.

We recruited developer participants from the unit responsible for building SE's current version. We interviewed 4 developers who had worked on SE in different capacities. Academic advisors were recruited by contacting academic advising offices and academic advisors across the university. We interviewed 8 academic advisors (4 female, 4 male), stemming from the College of Literature, Science and Arts (4), the School of Information, the College of Engineering (1), the Comprehensive Studies Program (1), and the Business School (1).

Undergraduate students were recruited via mailing lists across the university. For student participants, we aimed to balance gender and stratified with respect to major and year in program based on screening survey responses. Our resulting student sample was diverse in gender (9 female, 11 males), school year (4 in 1st year, 5 in 2nd, 5 in 3rd, 6 in 4th), and department (5 LSA, 5 Information, 5 Engineering, 5 Business).

In recruiting academic advisors and students, we did not disclose that our study aimed to understand concerns and issues with SE in order to limit self-selection bias. Instead, we recruited academic advisors to learn about " how SE can lead to student success," and students to understand "their academic advising experiences and perceptions of e-learning tools used in the advising context."

Qualitative Analysis Approach

All interviews were audio recorded and then transcribed using a transcription service. Interviews lasted 29–55 minutes (median: 36 minutes). Transcripts were checked for quality by the authors.

Developer interviews were analyzed using affinity diagramming, grouping individual quotes that revealed similar themes [28]. For the advisor and student groups, we conducted thematic coding [2, 33]. Separately for advisors and students, two researchers identified preliminary themes and created initial codebooks. Each codebook was then iteratively refined through independent coding and joint reconciliation until high inter-rater reliability was reached (Cohen's κ=.76 for both). Using the final codebooks, one researcher (re-)coded all interviews. The final version of the student codebook included 15 themes with 25 unique codes (e.g., "SE data accuracy" and "student consent"); the final advisor codebook had 15 themes with and 34 unique codes (e.g., "advisor access" and "SE basic usage pattern"). The final codebooks are available as supplemental material. Within larger themes, we then used affinity diagramming to identify more nuanced themes and categorize them within and across stakeholders to uncover thematic tensions and agreements [28].

5 FINDINGS

The findings from our multi-stakeholder interviews span four categories: context of usage, perceptions of stakeholders' SE access, data validity, and student consent and involvement. We observe that SE's use has evolved since it was deployed, being used by more people in different contexts than initially intended. Stakeholders have differing views on who should be able to access and use SE and why. Changes in use exacerbate transparency issues regarding the origin and validity of data in SE. Particular tensions arise between students and the other stakeholders with respect to student consent and whether students should be able to use SE as well.

Context of Usage

We find that advisors used SE in different ways, mostly depending on how SE fits best into their workflow, the types of undergraduate students they work with, and whether advisors actively use SE in advising sessions with the student. Despite different usage, all advisors shared the perspective that SE's main function and benefit lies in helping identify at-risk students early so advisors can provide timely support. We also found that SE's usage has evolved substantially with respect to its user base, training, and system ownership since it has been deployed. Students, on the other hand, were largely unaware of Student Explorer's existence before the interviews.

Advisors Have Different SE Usage Patterns. All advisors used SE frequently to check their students' performance, but in different ways. Five advisors showed students their performance in SE during advising sessions, often to prompt reflective discussion. Advisor 4 (A4) shared: *"like my last advisee, I'll pull [SE] up and we went over it just to have a more candid conversation about how she's doing in classes."* Three of these five advisors worked with students on probation, and used SE to make decisions on students' status (probation, drop, etc.). Through discussions with the students, advisors could verify the accuracy of SE's indicators and data, and encourage students to share their perspectives. Other advisors (3) preferred to check SE periodically to look for students who might need help. A2 stated: *"Once in a while I just scroll through here [in SE] and see who's got the exclamation points [red symbol]. And I use it kind of as an outreach to all"*. Most advisors commented that for them SE was part of an ecosystem of online systems that provide different student information (e.g., transcripts, class schedules, graduation requirements, and advising notes).

Developers exhibited a good understanding of advisors' different SE usages, due to feedback they had received from advisors during SE's pilot stage.

Inconsistent SE Training for Advisors. When SE was launched initially, the development team provided training for advisors. Over time, more advisors from a breadth of departments were granted access to SE, while the responsibility for SE was moved from a software development unit to an IT services group. In this shift, trainings were no longer offered, but there was also no consistent guidance on how advisors should use SE. Five of the advisors reported they learned by using SE. A4 noted *"There was never really formal training around how to use it,"* and A3 stated *"I pretty much figured it out myself."* The 3 other advisors received department-internal training, and found it helpful. This indicates that SE is not being introduced consistently to all advisors.

Advisors' Perceptions of SE. Most advisors described SE as a helpful and useful tool that makes their work with students more effective and efficient. Three advisors highlighted that SE allows for more honest and in-depth conversation, and provides a closer look at students' study habits. Advisors also talked about SE's impact on students. Some (3) recognized benefits such as how SE *"helps students focusing on what they need to work on in terms of straight grades"* (A3), and how SE is *"a source of data that allows the students to be supported from all realms"* (A4). Three other advisors saw more indirect effects on students, because *"it's only impacting the student on a one to one encounter [...] based on the students who come in and I show them [SE], some of them are actually really happily surprised [...] others are maybe disappointed"* (A6). A couple advisors (3) were concerned that SE might cause students to worry too much about their grades: *"so I can see that also having a negative effect on some students in terms of you know over-comparing themselves"* (A7). A2 shared that *"[SE] keeps us steeped in the culture of how close to 100 percent are you [...] so I think that's the negative. It seems like it's technology but really it's bringing us back to worrying about the second decimal point of somebody's grade."*

Interestingly, developers saw similar benefits as the advisors, but did not mention any negative impacts of SE, which is contradictory to prior research conducted by Neff et al. that academic engineering teams recognize the complexities of their work [39]. The developers instead focused on SE's broader impact, as examplified by D1: *"[SE] has been a huge value added to the learning analytics community. From that standpoint as well as being a tool that seats advisors in their role as students advocate and guide."*

Students Unaware of SE. In contrast to advisors and developers, none of the 20 student participants were aware of SE or its use of student data. When we introduced students to SE with screenshots, students saw SE as a good resource for both advisors and students. Most students (19) had a good understanding why the university has tools such as SE, from improving teaching, checking student performance, to better helping students learn and succeed. As S18 said: *"[the university] want[s] to maintain their prestige, and they really care about the students and they want them to learn [...] Maybe they can use this to [...] provide resources to help, because this is such a big university and some students don't know what they have access to."*

Advisors (7) who have shown SE to students reported positive, neutral, or inquisitive student reactions. A6 shared: *"[students] mostly like, not shock but just like, 'wow I had no idea that this exists. And can I have access to it?' That was the most standard response that students provide. 'You can see my grade?' "* Two advisors mentioned negative student reactions because students were *"weirded out"* (A8) that advisors can see student performance. The advisors who showed SE to students believed it helps make advising conversations more transparent and honest.

Surprisingly, most advisors (5) did not know whether students could access SE and three were not sure if students were aware of SE; five thought that students must be unaware of SE due to students' reactions to it. In contrast, developers expected students to be unaware of SE: *"The fact that its users are primarily advisors means that they are the people that are ultimately most aware of it [...] Part of that is that [SE] doesn't have a student facing interface. And so out of sight out of mind [for the students]"* (D1). D2 added even though students may not be aware of SE, they should know their data is used by the university: *"At some point they have signed an agreement with the university that their data will be used for research* *purposes, and to [...] improve educational outcomes. So it's a passive understanding."* However, none of the students recalled having been informed of SE and its data use. Some students speculated that they may have inadvertently agreed to it: *"I think I probably like signed a form somewhere when I came to [the university] saying that they could use my data [...] I am not sure"* (S16). D4 advocated for a more transparent approach regarding learning analytics: *"As we continue to develop applications like [SE], I think it's becoming increasingly important to be more transparent with students because we're tracking people in more ways than we ever used to."*

Perceptions of Stakeholders' SE Access

The second major emerging theme was tensions among stakeholders regarding access to SE and its data usage. Advisors, developers and most students had no concerns with advisors' use of SE, but some students stated a need for better student privacy protections. Most students believed direct access to SE could be beneficial to them; a view shared by only two advisors. Despite perceived benefits, some advisors and students were also concerned by SE's data-oriented presentation of learning progress, as it could stress students, inaccurately represent students, and incite privacy issues.

Advisors. Advisors' role requires them to access comprehensive student information in order to properly guide and support students. Thus, all advisors thought it is important for them to be able to use SE. Concerning student rights, some advisors (3) believed students should at least be informed about what data is used by SE, but should not necessarily be able to opt out. Two advisors were concerned that, given more control, students might be unwilling to share data with advisors. A5 noted: *"It would be my preference that we still have access to [SE] no matter what a student says."*

Most students (17) acknowledged advisors' need to access their academic information, including through SE. However, some students expressed privacy concerns regarding SE. Four students noted that privacy-conscious students might find it invasive for advisors to see such detailed learning information. Three students worried that the level of detail in SE might cause advisors to hold presumptions against students. S8 noted *"knowing such detail about a student's academic performance could create [...] biases when like the student is being advised."* One student pointed out millennials' "screenshot culture," i.e., the notion that everything can be easily taken a screenshot of and shared publicly. This student worried that if advisors could access SE from non-university computers there could be a risk of information leakage. Another student (S11) opposed advisors' use of SE as she explained *"I'm not very comfortable with [advisors seeing SE]. Cause, uh, I mean I feel like for people who are really not teaching the class, grades should be voluntarily provided instead of they have access to that."*

Students made various suggestions for improving student privacy in SE. For instance, students could explicitly grant advisors access to their information in SE. Rather than providing constant access to detailed student data, SE could notify advisors when a student's performance needs attention. Others suggested limiting advisors' SE access to students assigned to them.

Students. Many students (13) said that students should have access to SE. They argued that SE could help students track their own progress and address issues, better prepare students when meeting advisors, motivate students by comparing themselves to their peers, and assist students in gauging if the classes are right for them. Students also noted that the data in SE is *their* data, so they should be able to access and monitor it.

Only two advisors specifically advocated for giving students access to SE. They believed SE could help students work more efficiently with instructors and advisors on their academic plans, and reflect on their performance. The other six advisors either didn't mention or hesitated due to their unawareness of student access. A7 worried that SE could have *"a negative effect on some students in terms of over comparing themselves, or not understanding that their circumstances aren't the same as everybody else in the classroom."* Two developers explained that student access was considered during SE's development, but ultimately not realized due to potential risks of *"telling a student that they're in trouble without giving them any help or that sort of context or advice around what they should do"* (D1). Five students expressed similar concerns, they considered that SE might *"put more pressure on a student"* (S4) or *"indicate [students'] superiority or inferiority academically. It's not healthy"* (S1). Three students said SE could be demotivating for under-performing students. Four students thought algorithmically labeling students was unfair: *"I can see a lot of students being upset and say like 'Oh I'm not a red student, and I'm who I am,' and that's not right for a system to get to mark me like this"* (S19).

Other Stakeholders. Students mostly associated instructional roles with their academic life. Some students (8) suggested faculty and instructors should have access to SE to easily monitor students' academic performance and offer guidance. Four students added instructors should only see students' performance in the classes they teach. Although graduate student instructors (GSIs) and teaching assistant (TAs) are also part of the instructional team, students had contrasting opinions on whether they should have access to SE. Three students argued for SE access by GSIs and TAs because they are serving in a student supporting role; whereas two students were strongly against GSIs and TAs accessing SE, because they are peers. S11 pointed out: *"TAs usually go to the same school with you. And it's pretty weird. I mean worst case you might personally know the TA as a friend, so that's really awkward."*

Three students further mentioned that developers and other indirect stakeholders (e.g., administrators) should only see anonymized student data in SE, because *"having a random person knowing my grades and [...] being able to look up my grades, access information about me. I wouldn't like that"* (S6). S19 said: *"[developers] shouldn't have [access to] any [student] names, IDs, any identifying things, and they probably should have the classes blacked out too."* Two students further stressed that SE should ask students for permission first if certain stakeholders are accessing it.

Data Validity

SE obtains its data from the university's LMS. However, participants noted that how the LMS is used by instructors and how they enter data into the LMS affects data quality in SE, potentially resulting in inaccurate data and an incomplete representation of student performance in SE. These data validity issues are exacerbated by a lack of transparency about data quality and data limitations within SE.

Inaccurate and Inconsistent Data. All advisors commented that SE's data is often not fully accurate. Most (6) attributed this to SE drawing data from the LMS, which is not used in all classes and instructors may not always enter grades in a timely manner, which can result in data in SE lagging behind students' current performance. Even though no advisor fully trusted SE's data, all of them still used SE as a criterion to decide which students to reach out to and when, and to frame advising conversations. A8 stated: *"It's a way to begin a conversation. But in what I perceive as, like, the unevenness in which [...] instructors use [the LMS] or enter the data [into the LMS], I can't hold fast to it, kind of use [SE] with a grain of salt."* Three advisors echoed this view and noted that they compensated for potential inaccuracy in SE data by using SE in a careful, intentional way. A7 said: *"[SE] not being 100 percent reliable I think is ok, because it gets me looking a little bit deeper and double checking myself. But if somebody was to just blindly trust it I don't think that would work out well."* A6 noted the importance of asking the student for their perspective: *"it's really important to ask the student [what they think of the data in SE] you know and I will. The student is always curious to see [SE] but will often educate me [about what the data means]."*

Developers also acknowledged data quality issues due to different LMS usage. Even though students only learned about SE in the interviews, almost all had doubts about its accuracy based on their experiences with the LMS. Like the advisors, most students (12) questioned that the LMS can provide consistent data for SE.

Most advisors (6) expressed that the inaccuracy of SE data resulting from inconsistent LMS input relates to instructors' not realizing how their LMS use affects academic support systems like SE. A7 explained: *"honestly the biggest improvement would be if there was consistency with how instructors are utilizing [the LMS]. You know if you are going to have your course on [the LMS] make sure that you're maintaining that, so that the records that Student Explorer are pulling is the most accurate it can be. And I think that would come with time and faculty just getting used to you know doing things with the online course sort of aspects."* A6 suggested informing faculty about how LMS data is used outside of their course: *"further educating the faculty and how they are using [the LMS][...] maybe faculty don't even know that we are actually pulling [SE] up with our students and using it as a data point to help them."*

Incomplete Representation of Student Performance. Because of the potentially incomplete and inaccurate data, most advisors (6) did not see SE providing a complete representation of student performance; A2 said: *"as long as you accept that assumption that [the LMS] isn't the whole story you can only learn so much."* Half the advisors (4) reasoned about the benefits and limitations of SE in this respect: *"[SE] allows advisors to get a sense of where the student is in a class but it's not perfect"* (A1) and *"the initial warning signs allow advisors to quickly go through roster to see who might have a problem, but you can't trust it implicitly"* (A7). Three advisors emphasized that dealing with this issue requires engaging in *"conversations with the student, it's essential that the student be able to tell their side of the story"* (A7) to avoid *"judgments and assumptions based on this one slice of data"* (A7).

Two developers agreed that SE cannot show advisors the whole story. D1 said: *"[SE] may not be an accurate reflection of how much trouble [students] are in at any particular moment depending on the construction of the class [...] and the system completely falls over when you start to think about gameful courses,"* which allow for more flexible and personalized learning experiences. Two developers suggested that capturing even more detailed student activity data could enable a better reflection of students' performance.

Three students thought SE's comparison of students' performance to the course average provides a good surface-level sense of a student's relative standing in a class. However, on a deeper level, all students expressed that SE neglects many other aspects affecting learning outcomes, such as students' classroom participation and engagement (7), actual ability to perform (S17), career interest (S1), soft skills (S13, S18), instructors' evaluation (3) and impacts from students' personal life (S20). S7 also insisted *"nothing is a complete representation [...] test scores don't necessarily equate to learning."*

Insufficient Information About System. Advisors found SE generally easy to understand and navigate. However, five advisors were not sure how to distinguish the meaning of the red and yellow symbols, and they were unclear on how the colors were determined. A2 questioned: *"did somebody sit down and decide you know for this class this is where the red [symbol] would start. Or is it standard for all classes?"* A3 pointed out that *"there's no message conveyed about [students'] learning. It's all about the grade."* As a result, most of the advisors (6) have to develop their own interpretations on how to read SE's interface. Some advisors (5) suggested improvements for SE's transparency, such as providing clearer information on the criteria behind colored symbols (A4, A8), information on how students' grades are determined for a course (A2), guidance on interpreting students' performance (A6), and signals for data's validity and accuracy (A7). In comparison, all developers could clearly articulate the meaning of the colored symbols and did not consider that there might be a need for more explanation.

Most advisors (6) had experienced situations where SE did not function as expected, and noted a lack of technical support. A5 recalled having been pointed to different departments before a technical issue was resolved. From the developers, we learned that SE's ownership had transitioned to an IT service department — a fact that was not transparent to advisors. Even though SE had been deployed for several years, three advisors had the impression that SE was still under development and expected further improvements.

Student Consent and Involvement

Stakeholders had diverging opinions on whether and how students should be informed about SE and the level of involvement and control students should have. Most students and some advisors argued that students should be informed about SE, but who was responsible to inform students and how was a topic of debate. Stakeholders also differed in their views on whether students should have a say in whether and how their data is used by SE. While students suggested an opt-out and other privacy controls, advisors and developers thought it was more "complicated."

Obligation to Inform Students. Many students (11) thought they should be informed about SE's use of student data. Two students expressed that information would not matter: *"there are so many platforms and levels of authority who had access to our grades and performance that you don't even know about that, it doesn't impact us"* (S3) and *"as long as your data isn't shared with anybody else, I think it's ok if people in the advising office use a platform like this without notifying you beforehand"* (S7). Three students believed *"it might be nice to know if [SE] is being implemented, but I don't think [...] it would be too much of a uproar"* (S15).

Some advisors (4) also expressed that it would be fair to inform students about SE's use of student data. They suggested that such information should be provided as part of the LMS or courses: *"at the [LMS] level you could say to the student 'some of the data from your classes is available to [...] advisors' "* (A2) and *"that should be part of the course description [...] so that a student could make a conscious decision of 'I am taking this class it is going to be using Student Explorer data' "* (A7). A4 suggested that instructors (who are likely not aware of SE either) *"in the first day class [...] could talk about [SE] as just another data point and a vehicle to help students stay on track."* A6 assumed the university must have already informed students about student data use: *"I'm imagining that since we're using Student Explorer, those students must have agreed to it somewhere. No? (laugh)."*

Diverging Views on Students' Control Over SE Data Use. Students' perspectives on whether they should have control over SE's data use fell into three distinctive groups. Most students (12) argued for student control because *"this is a student's education and they should be [...] in charge of whatever relevant information regarding their academic career holds"* (S1). Students suggested specific solutions such as sending students emails requesting e-signature authorization for data usage (S8, S11, S18), having SE incorporate privacy settings and send notifications whenever student data is used in new ways (4), informing students about SE's benefits to increase their acceptance of data usage (S8, S13), and anonymizing student information in SE except for advising (S11, S16). These suggestions indicate that students are mostly looking for involvement in the decision rather than for ways to opt-out.

Four students did not think students should be able to decide how their data is used as it would undermine SE's data quality and benefits for students. S19 explained: *"if it's university policy to use this for advising, it would make sense to have as much information as you possibly can, because then the algorithm can learn better."* S3 thought SE's use of student data benefits students so there's no reason for students to have a say. S12 shared this view: *"I don't think user should decide, coz the purpose of such tool may not be obvious for such users [...] their initial thoughts may totally against the ultimate purpose of the system."* The remaining four students had no particular opinion on student consent, either because they felt student data is already used by the university and relevant stakeholders anyway, or they could not relate SE to themselves because they were not at-risk students.

Of the advisors, three recognized that students should have a say regarding student data use, but noted that due to advisors' responsibilities it is important for them to be able to check on students' situations. A4 shared: *"I get the student* *input [...] but I also think that there is some data that is kind of need to know, and, could be compromised in how we support students if students were adverse to that data being shared."* A3 also stated that *"beyond advisors yes [student should have a say], but it's important for advisors to be able to see how students are doing."* Four advisors saw both sides but did not know how to reconcile them. Two advisors considered an opt-out option for students reasonable, but considered it not the advisors' decision to make. A4 said that is a conversation for *"someone who has a higher pay grade than me."* A2 believed the Institutional Review Board should be responsible because they know the regulations of how student data should be used in learning analytics. Only A3 argued clearly that students should be able to *"opt out if they choose to."*

Developers saw themselves as good stewards of the student data but considered questions of student consent and involvement beyond their responsibility. D4 explained: *"This is part of a larger conversation about a student's ability to kind of opt in or out of the types of things that are being tracked about them at the university,"* and would therefore have to involve university leadership.

Students more broadly expressed the need to be involved in the learning analytics processes, through advisors' notifications (S9), LMS announcements (S8), orientation info sessions (S19), advising emails (S16), and the university. However, six students had mixed feelings about the university being responsible for enabling student control with respect to learning analytics; four expected the university should be accountable for using students' data only for good, the other two thought the imbalanced power relationship between students and the university would result in few choices for students. S15 summarized this resignation: *"I think part of it is trust, part of it is kind of resignation [...] [the university] had my information and they can kind of do with it whatever they want. [...] I could stay distrusting but it just gives me personally more peace of mind to say like well you know might as well trust them, they seem like they know what they're doing"* (S15).

6 DISCUSSION

Our findings show SE's evolution regarding its users and context of use. We also identify multiple tensions among and within stakeholder groups regarding the knowledge, access and use of SE. Moreover, advisor and student participants had varying levels of concerns due to the lack of transparency in SE's data source and validity. Students expressed their privacy concerns and desire for control about their data and involvement in the learning analytics process, but who should be responsible for involving and informing students and how was a topic of debate.

Limitations

Due to the qualitative nature of our multi-stakeholder analysis and the focus on a specific early warning dashboard, Student Explorer [32, 34], we refrain from drawing conclusions on the prevalence of the identified issues. We also acknowledge that other tensions or issues may arise in the context of other learning analytics systems, and caution that while the traffic light visual metaphor is a common one for early warning systems, other systems may have gone through different development and consultation processes, and may handle student data differently. However, our research surfaces tensions that arise among stakeholders in the context of deployed learning analytics systems, and we are confident that our findings provide insight for the design, development, and deployment of such systems.

Most student participants did not consider themselves at-risk students. They reported primarily going to advising sessions for matters related to course and graduation requirements rather than discussing grades. At-risk students and students on probation, who are the intended benefactors of SE, were more difficult to recruit given the precariousness of their academic situation. Further, our subjects were all recruited from a single institution where the application was deployed. Different institutions may have a different culture, student body, and policies and practices regarding academic advising or student data. As a result, our findings may not be representative of at-risk students. Nonetheless, our student participants' perspectives were still valuable in illuminating issues and tensions associated with learning analytics systems deployed in higher education.

A potential limitation is further that we did not interview other stakeholders, such as researchers and course instructors. We decided to focus on stakeholders directly involved in the advising process with SE: students, whose data is used by SE, academic advisors as the primary users of SE, and the developers responsible for the deployment of SE. It may be worthwhile to expand future multi-stakeholder analyses to include perspectives from additional stakeholders.

Implications and Recommendations

Based on the findings of our multi-stakeholder analysis, we provide recommendations for the design and deployment of learning analytics systems.

Design for Evolution. Our findings show that the use cases for Student Explorer have evolved over time, with advisors using SE in different ways, some of them not initially intended (e.g., advisors showing Student Explorer to students to ground a conversation on grades). Our results align with prior work showing that new learning technologies might encounter unintended use [48] and that users might disrupt a new system's usage practice when adopting and incorporating it into their workflow [13]. In particular in educational settings, designers and developers should be careful and comprehensive when considering how the learning analytics system might be used in practice, while allowing room for flexible use. For instance, considering the potential that students might be shown SE's dashboard by advisors could have resulted in a design that is less utilitarian and data driven in favor of better conveying a student's performance with respect to a course's learning goals.

Our findings regarding changed use and access to SE as well as advisors' inconsistent training experiences, show that design and research efforts should extend beyond pilots and continue into a system's operation. Once deployed, the use of a deployed learning analytics system should be periodically assessed in order to identify changes in use and whether made assumptions still hold, in order to reason about required adjustments to the system design or functionality.

Furthermore, our findings show that learning analytics systems should be designed such that related training and informational resources are integrated into the tool, either as a "help" page or better through cues and information integrated into the user experience. A reliance on external knowledge transfer and training, as was the case with SE, poses the risk of institutional knowledge being lost in personnel transitions or as responsibility for a system moves among units. The fact that many advisors were not clear on how the data in SE is generated or how to interpret different color indicators and thus had to develop their own interpretations further underlines the need for transparent explanations on what data a learning analytics system ingests, how the system reasons about the data and how outcomes should be interpreted.

Convey Data Validity. Our study showed that advisors did not fully rely on SE's data, and instead engaged with students to understand SE's output and the student's actual learning progress. These findings also show the importance of providing clearer information about data sources and validity within the learning analytics system. In the case of SE, advisors can reach out to percieved at-risk students and validate data accuracy through conversation. This option may not exist in all learning analytics contexts or advising functions. Ideally, learning analytics systems should have clear, informative and easy-to-interpret interfaces [19], present adequate data, and allow for accurate interpretation of this data [17]. In particular when learning analytics systems reason about data and classify students or learning progress in a way that is meant to inform decision making, data displays should also include indicators of confidence or uncertainty with respect to the data sources and the reasoning results. In our particular study not only were these indicators of uncertainty absent in the visual interface, but the underlying determinants of the data were unknown to the users, making the algorithms completely opaque and difficult to audit.

Involve All Stakeholders. While Student Explorer touches multiple stakeholders directly or indirectly, the focus in the system's development has been on the primary users: academic advisors. However, our findings underline the importance of considering and involving all stakeholders, as also identified by prior work [7, 46, 47]. Students' lack of awareness regarding SE clashes with their interest in being involved in the learning analytics process. Instructors are generally unaware of SE, but their involvement has the potential to positively affect SE's data quality as the core data source for SE is the learning management system (LMS). Thus the dependency between the LMS and early warning systems should be acknowledged, and the stakeholders responsible for (and aware of) the data from the former should not only be consulted in the design and deployment of the early warning system, but be aware of the uses of educational data they produce and its impact on data quality in other systems. Bi-directional understanding of the dependencies among educational systems is essential for all stakeholders in learning analytics ecosystems.

We advocate to recognize and value the role each stakeholder group plays in the educational process. Involving all stakeholders in the learning analytics process and considering their expectations and concerns can help maintain transparency, fairness, and ethical use of student data, as well as promote communication and understanding among stakeholders regarding the (in)completeness of data-driven representations of learning progress and outcomes. Moreover, bringing in all stakeholders (e.g., students, instructors and advisors) during the design and development phase of learning analytics can help more comprehensively identify use cases and scenarios, which is critical to promote efficient and satisfying user experiences with the system [51]. While it is important to involve admins, learning analytics maintainers, developers, and institutional management during the operation and use of learning analytics systems [22], key stakeholders in the learning process, namely students and instructors, need to be involved in the deployment phase as well in order to ensure the consistent, appropriate and transparent use of student data.

Recognize Student Consent and Involvement. Students need to be recognized as stakeholders in learning analytics systems. Our student participants wanted to know how their student data is used and have a say in that decision. This aligns with findings from prior work. Drachsler and Greller's survey showed that most of their participants believed privacy issues and ethical use of student data must be properly addressed to ensure acceptance of learning analytics [15], and that informed consent by students and options for them to opt out help facilitate and maintain trust among stakeholders [16]. Notably, while our student participants wanted to have a say, they saw the benefits of SE and did not indicate that they would want to opt out categorically, instead they desired involvement and a "seat at the table."

Rather than simply giving students complete control over student data or full access to learning analytics systems, we advocate for a more collaborative approach to address concerns over student involvement. For instance in the context of SE, if advisors identify unusual student performance and want to access more detailed information, SE could provide the option to "invite the student to the conversation," sending an access request to the student, possibly with a personal message from the advisor. This way, students become active participants in the learning analytics process, and are able to contextualize data (e.g., indicate that the requested LMS records are incomplete for a specific course) rather than being mere data subjects. Prior research has shown that student-facing dashboards enable student autonomy, increase student awareness, motivations and learning reflections [6]. Thus, ealry warning systems could provide a student-tailored view that helps students self-monitor their academic progress, integrating support and resource options like "connect to advisor." This would not preclude advisors from proactively reaching out to struggling students, but it would reduce the information asymmetry between stakeholders by making students aware of the dashboard's existence and enabling them to leverage it on their own. Finally, many universities already have a web portal, centralizing a variety of information, transactions and services [59]. Such web portals could incorporate information on student data use, this might include explanations of how, what, where, when, why and by whom student data is used, a student data usage log, as well as privacy settings for students, which instead of focusing just on opt-in or opt-out could provide students options to receive notifications on certain data uses, as well as inspect and possibly correct student data.

7 CONCLUSION

Our multi-stakeholder analysis of a deployed early warning dashboard revealed both agreements and tensions among stakeholders' perceptions and concerns regarding the access, use, and analysis of student data. Our findings underline the need for designing learning analytics systems with evolving use in mind, including recurring assessment of how the system is used. Designers should engage all stakeholders not just in the design and development of learning analytics systems, but also during operation and deployment in order to identify tensions and address stakeholders' needs and concerns. Particular attention needs to be placed on properly conveying data validity and confidence in data sources and reasoning outcomes, as well as explaining the reasoning process to stakeholders. Students, who are commonly the subject of learning analytics, should be given more attention and be involved properly in decisions regarding student data. Rather than opting out, students want to and should be involved in shaping the learning analytics process.

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