Chapter 13: Teacher and Student Facing Learning Analytics

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ABSTRACT

Learning analytics systems are increasingly being designed for and implemented in classroom teaching and learning in K-12 and post-secondary contexts. For analytics to play a constructive role, it is important to consider how they are being used by teachers and students and how they can be designed to enhance and complement human decision making. In this chapter, we first discuss issues that teachers and students face in the sensemaking of learning analytics systems as well as in the subsequent phase of acting on the information provided by such systems. We then discuss the following aspects for teacher facing and then student facing analytics: (a) theoretical models underlying analytics use; (b) ways analytic systems have been designed and implemented; (c) evidence of impact the systems have had on teaching and learning. The chapter ends with an overarching discussion of challenges that concern both teacher and student facing analytics and introduces the possibilities for co-design of analytics systems to address some of these challenges.

Keywords: Student facing analytics, teacher facing analytics, learning analytics systems, learning analytics dashboards, learning analytics use, self-regulated learning, sensemaking, learning analytics design, human-centered learning analytics, participatory design of learning analytics

Much of the work of learning analytics designers and researchers revolves around challenges of how to extract, process, and present data in ways that are useful to educational stakeholders. However, system design alone does not ensure successful uptake [26, 24, 32]: "analytics exist as part of a sociotechnical system where human decision making and consequent actions are as much a part of any successful analytics solution as the technical components" [84, p. 4]. Thus, learning analytics designers and researchers need to attend to the human activity of working with these tools in their various contexts of use. In this chapter, we specifically address the use of learning analytics systems by teachers[1] and students. We first discuss issues in making sense of and acting on information provided by learning analytics systems. We then detail, first for teachers and then for students: (a) theoretical models underlying analytics use, (b) ways systems have been designed and implemented, and (c) evidence of the impact these systems have had on teaching and learning. We conclude with a focus on obstacles and opportunities to the development of effective and adoptable tools.

[1] Throughout this chapter we use the term teacher generally to refer to those holding instructional roles in both K-12 and post-secondary education.

1 IMPORTANT CONSIDERATIONS FOR LEARNING ANALYTICS USE

Using learning analytics effectively involves making sense of the information presented *and* taking action based on it [77, 15]. While analytics are often developed for use across a range of situations, the answer to questions of meaning and action are inherently local. In the case of teachers and students, the design of learning analytics systems needs to be sensitive to the anticipated contexts of use (e.g. daily classroom routines) and potential unintended consequences of use (e.g. taking student metrics as a proxy for teacher competence). Wise and colleagues [96, 95, 93] have pointed to several well-documented issues in using analytics to inform educational decision-making that relate to processes of interpretation and taking action. These considerations must be taken into account by those designing learning analytics systems and those implementing them for use of the systems to be effective.

With respect to interpretation, analytics are abstracted representations of past activity, yet intended to inform concrete future activity. This makes it critical for users to have an understanding of the context, purposes and processes of the learning activity in which the analytics were generated and a means by which to connect this information to possible future action [50, 27]. Most people are aware of the fact that actions in digital spaces leave trace data. The conceptual leap is understanding how the high level representations of learning activity shown in analytic systems are produced from these data. In addition, there is the question of what reference point the data should be compared to (e.g. a pre-determined standard or relative values for peers, [95]). Even when information is understood, it may not be believed as accurate, relevant or useful [42, 96], thus questions of trust and validity present additional consideration for the interpretation of analytics [15, 52]. Another limitation is that analytic systems tend to provide the same kinds of metrics over time; however, different information may be more or less relevant to different parts of the learning process [92]. Finally, students and teachers each have their own goals for learning; thus designers cannot rely on a one-size fits all solution to be relevant for everyone [82]. Students and teachers need to prioritize the relative value they assign to the available analytic feedback.

With respect to taking action, there are two core issues. First, analytics provide a retrospective lens to evaluate past activity, but do not always indicate how to make changes to the situation in the future. For example, a social network diagram can show that a certain student is not receiving replies from their classmate without providing information about what would encourage greater responsiveness. Second, even when desirable action is identified, most change does not occur instantaneously — incremental improvement and intermediate stages of progress are often required. For example in Wise, Zhao and Hausknecht [97] students took multiple cycles of goal-setting and feedback to change their learning behaviors. Action may also be deferred when teachers (or students) are not certain of their interpretation and want to wait for more data to become available [94]. These issues have consequences for analytics design and implementation. To support teachers and students, designers cannot assume that providing data alone is enough. Support is needed to translate information on past activity into future action (and track progress towards this goal) either as part of the analytics system or the surrounding practices with which it is implemented. It also means that when studying use of analytics systems, researchers may need to take a longitudinal approach to reveal changes that happen incrementally over time rather than directly after dashboard use. It is also important to consider the larger culture of trust and transparency around analytics amidst concerns of surveillance. Teachers may fear that their data can be used by administrators to assess performance or compliance with mandated standards [35, 35]. Students are often unaware of how they are being monitored, why, and who can view this data [79]. If data processing prior to analytic presentation is "blackboxed," teachers and students may perceive that the collection of these data is primarily designed for the benefit of the institution and be less likely to trust and use the information provided [78].

2 TEACHER-FACING LEARNING ANALYTICS

Teachers are a natural audience for learning analytics as they are already engaged in examining student learning to inform their practice. While such teacher-inquiry traditionally depended on qualitative methods (e.g. student observations, examination of learning artifacts; [16]), there is increasing interest in the use of quantitative data to inform the process [89]. Analytics can also be a powerful tool to help teachers with other dimensions of their practice, for example identifying and meeting diverse student needs [22]. While the discussion below focuses on cognitive and pedagogical models of use, research suggests that affect also plays a role as teachers may feel encouraged, disheartened or even upset about what the information tells them [94].

2.1 Theoretical Models of Teachers' Learning Analytics Use

One way analytics can support teachers is to inform *learning design*. Learning designs document teachers' pedagogical intentions, providing a conceptual frame for asking questions about learning activities and supporting sense-making of the information provided by the analytics [18]. Data can help teachers understand the effects of a specific instructional approach on student activity and learning [20], which in turn provides feedback to improve the design [65, 60]. Lockyer and colleagues [50] provide a specific model for aligning learning analytics use with learning design that describes how teachers can map the learning processes intended by their design, pre-identify patterns indicating (un)successful student engagement in the processes, and use analytics to track student progression towards the desired state (an absolute reference frame for interpreting the data; [94]). Setting incremental stages to target along the way or using prior activity to judge progress are other comparison strategies that can be employed. In addition to point-in-time judgements, temporal analytics can also be used for dynamic evaluation of learning progress [59].

Another way analytics can support teachers is by providing feedback on activities inside the classroom as they occur [85]. Here the analytics are used in (relatively) real-time as a tool to monitor activity, support the diagnosis of situations needing attention, and prompt teachers to offer support according to the students' needs. These analytics support *classroom orchestration* [69] in which teachers use data as continuous formative assessment to adapt learning at the classroom, small group, or individual level [41]. Several authors have provided descriptive models of how teachers make sense of the information provided and select a pedagogical response [54, 58, 85, 94]. In the first stage, analytics aggregate information for manageable presentation through visualizations comparing students' current activity to prior activity or absolute standards [85, 94]. To arrive at an interpretation of students' activities, teachers triangulate and contextualize the data with other information they have, noticing differences across individuals or groups, to answer goal-oriented, problem-oriented or instructional modification questions [49] . In the second stage, teachers use the information to inform pedagogical responses, which could be scaffolds targeted at the whole class, subgroups of students, or individual students. There is great potential for analytics to support teachers' classroom orchestration by enhancing their insight into the classroom situation, their confidence in this insight, and thus inclination to act [46]. In this way analytics enable teachers to make informed decisions that are aimed at students' needs in-the-moment [58, 85].

2.2 Teaching-Facing Learning Analytics Systems

The most prominent form of learning analytics for teachers thus far are dashboards: visual displays that provide information about students' activities and progress on the task at hand (for recent overviews, see [75, 47]). An important distinction in teacher-facing analytics is the amount of interpretational aid they provide [48]. Some early teacher dashboards left all interpretation to the teacher. For example, Schwarz and Asterhan [73] showed teachers information about students' argumentation in a collaborative learning setting, but did not prescribe when to intervene or what situations might need attention. Similarly, [58] reported on a dashboard that displayed information about individual student performance on mathematics exercises; teachers were free to decide how to interpret and use them for follow up interventions. Other teacher dashboards have gone a step further to provide alerts about the occurrence of problems that specific students or groups might be facing (e.g. [13, 30], or even alerts plus advice regarding what kind of problem students might be facing in a particular situation [86]). Most existing dashboards have focused on supporting teacher sense-making; however many teachers also experience difficulty in determining what action to take in response [75, 86]. While few dashboards have yet to explicitly target the action-taking phase of analytics use, there are some notable exceptions. For example, Olsen, Rummel, & Aleven [63] developed a system which advised the teacher on which students to pair up and when to switch to a different activity. In an earlier example, the Assistant program offered advice to teachers on what feedback to provide to students [14].

Teacher dashboards are a form of *extracted analytics*: data traces of students' learning activity are provided in an interface separate from the learning environment that generated them. An alternative is *embedded analytics*, when the data traces of learning activity are shown directly in the learning environment that generated them [92]. For example, Alavi and Dillenbourg [3] created ambient displays in the form of small lamps placed in the classroom that provided information on whether students had a question for the teacher and how long they had been waiting. In more recent work, Holstein, McLaren, and Aleven [34] developed augmented reality systems that displayed information visible through the teachers' enhanced glasses showing whether students were off-task or stuck on a problem.

Learning analytics can also play a role in supporting teachers by providing information not only about students but also about their own actions. Here the analytics take on a role of stimulating self-reflection, albeit with the same goal of optimizing student learning. For example, Anh et al [2] used small lamps on the tables of collaborating students to display how long the teacher had visited each group, thus providing information to the teachers about their circulation around the classroom. The lamps provided neutral information without enforcing or encouraging teachers to divide their attention equally - that decision remained with the teacher. Despite their potential, systems that advise on specific teacher behaviors are rare and hard to design since the impact of teachers' actions can be very context-specific.

2.3 Use and Impact of Teacher-Facing Learning Analytics Systems

The impact of teacher-facing learning analytics has largely been studied in terms of effects on teaching: teachers' perceptions of usability, their awareness of student activities, and the actions they may take as a result [86]. This is a complex process [93, 86] requiring specific competencies such as data literacy and the ability to integrate knowledge from the analytics with existing teaching knowledge [54]. Multiple studies have found that analytics increase the specificity of teacher diagnoses in their classroom [75, 47]. However, for teacher-facing learning analytics to have an impact on students, teachers need to act on these diagnoses by selecting appropriate response actions. A small number of studies have examined the subsequent actions teachers select based on their interpretation of the analytics. Molenaar and Knoop-van Campen [58] showed that when activating pedagogical knowledge in the sense-making stage, teachers use more diverse types of feedback in the response-stage. Wise and Jung [93] also showed diversity in teachers' responses to learning analytics, including a non-action response of adopting a "wait-and-see" posture. Xhakaj, Aleven, and McLaren [98] found that analytics use influenced teachers' subsequent lesson plannings (e.g. what topics to cover in a class session). Knoop-van Campen, Wise & Molenaar [43] found dashboard consultation led to relatively greater amounts of process feedback and that the difference was especially large for low-ability students.

Going beyond teacher actions, very few studies have yet to follow the prolonged causal chain to examine effects on student activities or learning. In one notable exception, Martinez-Maldonado, Clayphan, Yacef, and Kay [55] report a comparison of impact of two dashboards, one providing information only and one providing information plus alerts. Teacher interventions informed by the system with alerts resulted in an improvement in student learning, those informed by the system with information only did not. This study points to the importance of working towards studies that document the ultimate goal to impact students' learning.

3 STUDENT-FACING LEARNING ANALYTICS

Students are an important audience for analytics use, as their learning is the ultimate goal of educational systems and much of the data collected in learning analytics systems is generated by or about them. There is a presumption that students will benefit from exposure to their own learning data and many argue that students have the right (and responsibility) to review their own data [64]. As such, an increasing number of analytics systems are being designed to provide information about learning directly to students. These both follow and diverge from a long history of educational technologies used to provide feedback to students (e.g., cognitive tutors, [45]; homework practice and assessment tools such as Assistments, [57]; open educational resources such as Kahn Academy, [38]).

Learning analytics dashboards differ from prior feedback systems in a number of ways. First, other systems typically provide feedback about correctness of answers, whereas dashboards often combine performance feedback with information on students' learning processes (e.g., planning, tracking progress). Second, while other systems tend to provide relatively simple static feedback, dashboards offer visual displays which are often complex and/or interactive, allowing students to filter or select specific information. In addition, prior feedback systems typically provided information to students *after* they had finished a problem, activity or assignment, whereas dashboard information can be available on-demand, so students have flexibility and control of when they consult this information. Third, while many feedback systems benchmark using normative standards, in dashboards student performance is often also visualized in relation to that of local peers. Sometimes, students are also provided with information specifically in the context of "students like them" [40]. Finally, in cognitive tutors and similar systems, the computer is in control, whereas dashboards offer information to students, who decide on any possible follow-up actions. These dashboards are quickly becoming a standard feature in applications aimed at personalizing learning, such as Learning Management Systems, as well as in newer applications for personalizing learning like gameful approaches to pedagogy (e.g. Gradecraft [1]) and as part of tailored messaging systems (e.g. eCoach; [36]).

3.1 Theoretical Models of Students' Learning Analytics Use

Student-facing learning analytics aim to support students in conscious attention to and improvement of their own learning processes [93]. Feedback is provided in the context of dynamic cognitive processing whereby students select, adapt and generate tactics and strategies for learning and monitoring their learning [12]. Affective considerations come into play as well as how students use analytics depends not only on what the information helps them know, but also how it makes them feel [92, 42]. Although there have been calls for student facing learning analytics to be theoretically grounded with respect to pedagogy and learning (e.g. [74, 6, 7, 37]), most system designs are still driven primarily by available data. When theory does drive system design, models of Self-Regulated Learning (SRL) are commonly employed [56].

Zimmerman [100, p. 4] described self-regulated learning as students that are "metacognitively, motivationally, and behaviorally active participants in their own learning". This includes planning, monitoring, and evaluation of one's own learning, and using these strategies to achieve academic goals. As a positive relationship exists between self-regulation and learning performance [10, 90], SRL is seen as a promising way for learning analytics to support students by making these processes more explicit and allowing students to see and assess their own learning. Drawing on SRL theory, Wise [97] proposed a specific model of student learning analytics use involving goal-setting, action and reflection. These engendered four principles for pedagogical practice to support students' analytics use, with initial empirical validation in Wise et al. [96]: Integration, Agency, Reference Frame, and Dialogue. Later work by Klein et al. [42] validated the central importance of Agency in shaping students' relationships to analytics and offered four additional factors to consider in their sense-making: Accuracy, Relevancy, Trust and Relationships.

While SRL has been the dominant theoretical paradigm thus far, several other theoretical frameworks could also contribute to the system design for student-facing analytics. Expectancy Value Theory (EVT; e.g., [25]) posits students are motivated based on their expectancy of success, value, and cost of their options to accomplish learning goals. Investigation of dashboard use under EVT could reveal in which contexts students consider dashboards to have lower utility, and thus lower value, such as students taking a course to fulfill a requirement versus those who want to perform well (e.g [42]). Self-Determination Theory (SDT: e.g. [68]) posits that motivation is primarily based on the satisfaction of three needs: autonomy, relatedness, and competence. Based on SDT, dashboard design and evaluation could be oriented toward how effectively they contribute to students' need satisfaction. For example, students' motivation to engage with a dashboard may depend on their belief that it provides (a) a sense of control over their ability to accomplish course goals, (b) a greater sense of belonging within the course or discipline, and/or (c) information that increases their competence in meeting course requirements. Students who experience a higher level of control in the learning process are more likely to be intrinsically motivated and improve their performance [19] and dashboards may be an excellent avenue to provide students with a greater sense of agency and autonomy.

3.2 Student-Facing Learning Analytics Systems

Fritz [28] conducted one of the first wide-scale deployments of a dashboard specifically aimed at students, called Check My Activity (CMA), that allowed university students to compare their LMS activity and grades against their classmates. Student focus on grade views has been observed repeatedly, including Young's [99] analysis of students using a commercial LMS (Blackboard). Following Blackboard's design, Corrin and de Barba [17] created a dashboard with data on students' formative and summative assessment scores and their LMS engagement. Students were able to articulate and interpret feedback presented through a dashboard, but there was little evidence of students' ability to understand the connection between feedback and their current learning strategies. Wise and colleagues [92] implemented an analytics-enhanced discussion forum called Starburst that incorporated goal-setting and reflective prompts to encourage analytics use as part of an SRL cycle. Students' use of the analytics showed that comparison with peers played an influential — though not always positive —role on changes in behaviour, and students' mistrust in how some analytics were computed may have dampened use [96]. Khan and Pardo [39] implemented Data2U, a system providing students with feedback about their interactions with the online resources. They characterized different types of student dashboard use, providing insight into when different students utilize the dashboard (i.e. beginning, middle or end of a study session). However, there was no statistically significant relationship between students' use of the dashboard and their academic performance. Taking a participatory approach to analytics with a critical lens, Knox [44] developed the Learning Analytics Report Card (LARC) to give students choices about what data to include and exclude in the reports it generated. Most recently, Kia et al. [40] implemented a student dashboard into their campus' LMS, and found that students' SRL behaviors and academic achievement influenced how students used the dashboards.

3.3 Use and Impact of Student-Facing Learning Analytics Systems

There has been limited research exploring how students interpret and act on learning analytics and the resulting effects on their motivation, behavior, knowledge and skills [6, 74, 87]. This problem is not unique to learning analytics, however. Regarding the broad research on the effectiveness of feedback, Winstone [91, p. 227] points out "there are very few examples where researchers explore the use of feedback on a behavioral level, and even fewer examples where researchers collect data to follow up and see how students' engagement influences them later in time". With the notable exception of collaborative learning analytics (particularly group awareness tools, e.g. [5]), existing research on student-facing learning analytics systems has concentrated more on dashboard usability and usefulness, rather than an understanding how they support educational practices in the wild [29].

When *how* students use analytics is studied in authentic educational settings, their interactions with technology (e.g., counting views, files accessed, time on task) are usually the main marker of impact. For example, Wise [92] found the most common change that students made after the introduction of the analytics-enhanced Starburst tool was to increase the percentage of their peers' posts that they read. This is a behavior thought to contribute to learning theoretically (through increasing the diversity of ideas to which a student is exposed), but direct evidence of learning outcomes gains was not available. Further, only a few recent studies have investigated differences in how students use dashboard information [4, 33, 40], such as the particular tactics and strategies they take to work with the information [29], that may have important effects on subsequent outcomes. From these studies it is clear that the use and impact of student-facing analytics is a crucial topic for future research to understand how, when, and to which students we should provide these systems. In the preceding sections we described teacher- and student-facing learning analytics systems independently. However, there are important issues that bridge across these categories.

A central question for teacher- and student-facing learning analytics is what kinds of information is most useful to distribute across which parts of the overall system at different points in time. What support should analytics offer to students directly, which information is best passed to the teacher first, and which decisions can effectively be made by the analytics system autonomously? One example is suggested by Rummel, Walker, and Aleven [70] as they describe an "utopian" vision of adaptive support for collaborative learning in which the analytic system nudges a student directly to engage more with her partner during a learning task, supports her review and reflection on her engagement once the task is complete, and provides information and suggestions to the teacher for assigning her a subsequent collaborative partner and task. They also consider what analytic systems can learn from teachers and students to help them provide more useful information and/or guidance. This represents a move towards considering hybrid teacher-analytic and student-analytic systems as part of the classroom ecology.

In addition, the triangular interplay between teachers, students and analytic tools is a growing area of focus and research. Two particular issues to consider are symmetry (to what extent do students and teachers have access to the same kinds of information) and transparency (to what extent do students know what teachers can see). In situations where teachers and students are able to work with data jointly to improve learning processes, analytics can be seen to act as a third "voice" in the conversation between teacher and student [92]. For example, in two recent studies of teacher-facing dashboards at the university level, teachers expressed the desire to have a deidentified view of the analytics so they could show their students evidence about why they were concerned about their performance in the class [48, 94]. Analytics can also act as a mediational object for interactions between teachers and students as seen in Tan, Koh, Jonathan, and Tay [81] who documented a 9th grade school teacher sharing visualizations of her students' online discussion comment types and interaction network with them as an object to support collective reflection about the quality of their collaboration. Similarly, Lonn, Aguilar, and Teasley [51] described how when a dashboard designed specifically for academic advisors was shared in an advising session, it became a tool for advisors and students to talk about the student's academic progress. With the introduction of this third voice, a recalibration of student and teacher classroom roles is needed.

For students, analytics offer the opportunity to be explicitly prompted and supported to monitor and reflect on their learning, allowing them to develop metacognitive skills and take responsibility for their own learning. Research has shown that some students arrive in the classroom better equipped to make use of analytic information than others [53]; thus there is often a need to develop data literacy and self-regulation skills in tandem with analytics use. However, there is also a risk that providing too much information, automation or guidance (whether from the learning analytics systems or by the teacher) may create dependency, robbing students of the opportunity to display agency in their own learning. Educators worry about the rise of "helicopter analytics" where institutional tools and processes assume a decision-making role for students that many parents have been criticized for playing [35]. On the whole, a balance is needed to provide guidance that both helps students make better-informed choices in the short-term [62] and increases their ability to be independent learners over the long-term [9].

For teachers, analytics can provide essential insights to enhance their practice through optimizing learning design or improving on-the-spot decision making. Analytics should be designed to process information from many students at the same time and solve lower-level issues such as selecting appropriate follow-up tasks for a student. Doing so frees up valuable time that the teacher can spend on addressing higher-level support needs such as providing elaborate explanations or modelling effective collaborative behavior [72, 80]. Designing analytics to empower teachers will also mitigate concerns that the technology will undermine their role and responsibility in the classroom and cause them to feel forced to defend their own worth [86]. Goos [31] describes how teachers' professional identity includes their mode of working with technology (e.g. analytics) where it may be conceptualized as a partner, servant or enemy. Several authors have therefore argued for promoting teacher use of analytics as a *collaborative relationship*, leveraging the strengths of both teachers and technology [72].

4 CO-DESIGN OF LEARNING ANALYTICS AS A WAY FORWARD

One powerful route to addressing these challenges is to involve students and teachers in the design of learning analytics systems. Processes of co-design (or participatory design) address concerns that technologies might not meet the actual needs, context, and practices of the intended end-users [61, 8]. The shift can be described as a move from "designing *for*" to "designing *with*" [21] that generally involves multiple iterative cycles of ideation, development and testing. Adoption of co-design practices to develop learning analytics tools [87] is part of a recent shift towards human-centered learning analytics [76]. Co-design of learning analytics can involve users in decisions about the content of the analytics (what information is provided) and/or the visualization of the analytics (how the information is provided). When co-design is employed, it has most often involved teachers (e.g. [2, 23, 34, 55, 83, 84, 88]). Recent efforts have started to engage students in the process of analytics design as well (e.g. [67, 66, 71]).

The potential benefits of co-design are substantial: by giving teachers and students a role in the creation of learning analytics we are not only better able to design tools that fit their contexts and needs, but also allow them to surface their hopes and fears related to the use of analytics. There is a long tradition of work in HCI that can inform our processes of co-design (e.g. [21]); however there are also challenges specific to learning analytics, particularly varying levels of data literacy and asymmetric power dynamics. These issues may also intensify existing tensions in co-design for learning between what users want and what others want for them. Techniques from established co-design methodologies are being adapted for learning analytics to address such challenges [34, 66, 71]. A basic tenet of learning analytics is to provide information that is actionable by its users. Adopting co-design practices along with established learning theory makes it more likely that designers can discover what teachers and students need to do, and to provide them with information that helps them accomplish those goals. This is an important area for further development in support of adoptable, actionable and impactful teacher and student facing learning analytics.

In conclusion, for mainstream adoption of teacher and student facing learning analytics to become a reality [11], it is critical to establish a level of transparency and trust between developers and users of analytics. In addition, to be efficacious, analytics must be designed to fit with real world educational contexts and be validated through testing of use and impact in them. By engaging in practice-informed design and careful consideration of users' concerns as part of our research, we move towards the creation of learning analytics systems that truly impact teaching and learning.

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