Chapter 13: Learning Analytics Implementation Design

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ABSTRACT

This chapter addresses the design of learning analytics implementations: the purposeful shaping of the human processes involved in taking up and using analytic tools, data, and reports as part of an educational endeavor. This is a distinct but equally important set of design choices from those made in the creation of the learning analytics systems themselves. The first part of the chapter reviews key challenges of interpretation and action in analytics use. The three principles of Coordination, Comparison, and Customization are then presented as guides for thinking about the design of learning analytics implementations. The remainder of the chapter reviews the existing research and theory base of learning analytics implementation design for instructors (related to the practices of learning design and orchestration) and students (as part of a reflective and self-regulated learning cycle). Implications for learning analytics designers and researchers and areas requiring further research are highlighted.

Keywords: Learning design, analytics implementation, learning analytics implementation challenges, teachers-facing learning analytics, student-facing learning analytics

Much of the work of learning analytics researchers and designers revolves around the challenges of how to extract, process, and present data in ways that are useful to various educational stakeholders. However, after measures have been created and displays designed, there is still additional work required for analytics to play a constructive role in educational systems. System design alone does not ensure successful uptake (Ertmer, 1999; Hall, 2010; Donnelly, McGarr, & O'Reilly, 2011) as "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" (van Harmelen & Workman, 2012, p. 4). Thus, learning analytics researchers and practitioners need to attend to the human activity of working with these tools and develop a knowledge base for the design of learning analytics implementations (see Figure 13.1).

DEFINING LEARNING ANALYTICS IMPLEMENTATIONS

This chapter focuses on the elements shaping how learning analytics are motivated and mobilized for productive use by instructors, learning designers, and students. The act of introducing learning analytics into an educational environment is called a learning analytics implementation. While the term "learning analytics intervention" has also been used in the past (Lonn, Aguilar, & Teasley, 2015; Wise, 2014), it is a more narrow label that implies learning analytics use as an interruption to regular learning practices that occurs at a specific point in time to address a problem. Implementation is preferred as a more general term that also includes ongoing learning analytics use as a sustained activity incorporated into habitual learning practices (Wise, Vytasek, Hausknecht, & Zhao, 2016). Learning analytics implementation design is then defined globally as the purposeful framing of activity surrounding how analytic tools, data, and reports are

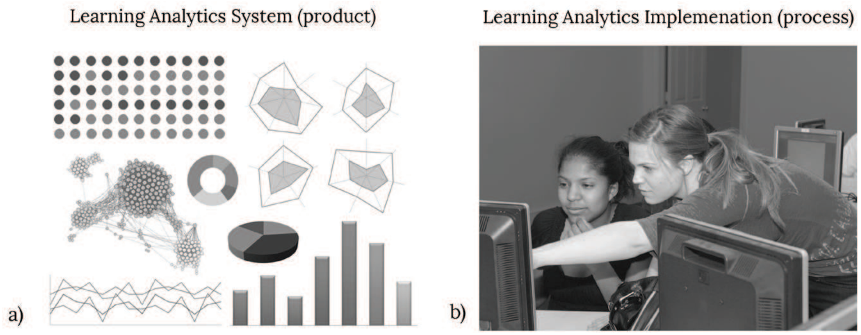

Figure 13.1. Visual differentiation of a) a learning analytics system (product) and b) intentional use of the system by instructors and students (process). Design of the former addresses issues of measures, algorithms, and displays while design of the latter addresses issues of timing, interpretative lens, and action parameters. Source: Photo in b) by US Department of Education licensed under Creative Commons Attribution 2.0 License. Cropped from original (www.flickr.com/photos/departmentofed/9610345404)

taken up and used as part of an educational endeavor. Specifically, it addresses questions of who should have access to particular kinds of analytic data, when the analytics should be consulted, for what purposes, and how the analytics feed back into the larger educational processes taking place.

USING IMPLEMENTATION DESIGN TO ADDRESS LEARNING ANALYTICS CHALLENGES

The process of using learning analytics involves making sense of the information presented and taking action based on it (Siemens, 2013; Clow, 2012). While analytics are often developed for general use across a broad range of situations, the answer to questions of meaning and action are inherently local. Correspondingly, the design of learning analytics implementations needs to be more sensitive to the immediate learning context than the design of learning analytics tools. This is seen in several well-documented challenges in using analytics to inform educational decision-making at the level of *interpretation* as well as at subsequent stages of *taking action* (Wise & Vytasek, in preparation; Wise et al., 2016).

At the level of interpretation, two important challenges are those of context and priorities. *The challenge of context* refers to the fact that analytics are inherently abstracted representations of past activity. Interpreting these representations to inform future activity requires an understanding of the purposes and processes of the learning activity in which they were generated and a mean by which to connect the analytics to these (Lockyer, Heathcote, & Dawson, 2013; Ferguson, 2012). *The challenge of priorities* refers to how users assign relative value to the variety of analytic feedback available. Particular aspects of analytic feedback may be more or less important at different points in the learning process and different analytics can provide information that suggests divergent interpretations that must be reconciled (Wise, 2014).

At the stage of taking action, two important concerns are those of possible options and enacting change. *The challenge of possible options* refers to the fact that analytics provide a retrospective lens to evaluate past activity, but this does not always directly indicate what actions could be taken in the future to change the situation. *The challenge of enacting change* refers to the question of how and on what timeline these actions (once identified) should occur. Change does not occur instantaneously – incremental improvement and intermediate stages of progress need to be considered.

Implementation design helps address these challenges by providing guidance at the mediating level between the analytics presented and the localized course context. This both provides the additional support required to make the information actionable and allows for tailoring of analytics use to meet the needs of particular learning contexts.

IMPLEMENTATION DESIGN CONSIDERATIONS

Learning analytics implementations operate at the interface between the learning activities (the pedagogical events that generate data) and the learning analytics (the designed representations of this data). This relationship can be considered through three guiding principles: Coordination, Comparison, and Customization (Wise & Vytasek, in preparation) grounded in theories of constructivism, metacognition, and self-regulated learning (Duffy & Cunningham, 1996; Schunk & Zimmerman, 2012).

The Principle of Coordination

The principle of Coordination is the foundation of learning analytics implementation design, stating that the surrounding frame of activity through which analytic tools, data, and reports are taken up should position the use of analytics as an integral part of the educational experience tied to goals and expectations (Wise, 2014). To be coordinated with the learning activity, the use of learning analytics needs to be conceived of as a central element of the learning design itself (Lockyer et al., 2013; Pardo, Ellis, & Calvo, 2015; Persico & Pozzi, 2015) so that it is clear to the user how the analytics are meant to play a role in their regular engagement in the learning process.

Conceptual Coordination means an advanced consideration on which of the available analytics to focus (based on the goals of the educational activity) and what productive and unproductive patterns in these metrics are expected to look like (Brooks, Greer, & Gutwin, 2014; Macfadyen & Dawson, 2010; Persico & Pozzi, 2015). To represent the breath of valued actions during a learning activity, it is advisable to use diverse analytic measures (Suthers & Rosen, 2011; Winne & Baker, 2013). It is important to clearly communicate the logic of this connection tying pedagogical goals with learning actions and data-based feedback to the analytics users (Wise, 2014) as initial evidence suggests they put more value on metrics when they clearly understand the connection to learning (Wise, Zhao, & Hausknecht, 2014).

Logistical Coordination means attention to when and how it makes sense for users to work with the chosen analytics as part of the teaching or learning activity. With experienced learning analytics users or those with strong self-monitoring skills, it may be fine to provide only Conceptual Coordination and leave room for individual decisions around when to consult the analytics (van Leeuwen, 2015). However, in many cases, explicit guidance about when and how to work with the analytics as a tool to support learning or teaching is necessary (Koh, Shibani, Tan, & Hong, 2016). General strategies include suggesting a rhythm of analytics use (Wise, Zhao, & Hausknecht, 2013) or a timescale for checkpoints (Lockyer et al., 2013); specific approaches for instructor and student use are discussed in sections 5 and 6.

The Principle of Comparison

The principle of Comparison addresses the need for one or more appropriate reference frames with which to evaluate the meaning of an analytic. For example, the interpretation of a student receiving a particular knowledge assessment (say "25") varies depending on the highest possible score, the performance of the rest of the class, and the level of their prior achievement.

Absolute reference frames for learning analytics provide a fixed standard for comparison that has been set in advance; for example, a set of course expectations (Wise, Zhao, & Hausknecht, 2014). Absolute reference frames can vary in the specificity of the standard set by providing an exact target for a metric or a range of desirable values.

Relative reference frames provide a variable standard that fluctuates over time. One relative reference frame is *peer activity*. This commonly used reference frame sets up comparisons across individuals based on a measure of central tendency or distribution (Corrin & de Barba, 2015; Govaerts, Verbert, Duval, & Pardo, 2012). Another relative reference frame is *parallel activity*, in which comparisons are made across learning events within a course or across courses (Bakharia et al., 2016). In this case, it is critical that the activities being compared are indeed parallel in key ways (e.g., duration, intent, expectations), otherwise the comparisons made may lead to invalid inferences. Finally, a less commonly used but powerful reference frame is *prior activity*, in which comparisons are made for the same individual(s) across time, allowing for the tracking of progress and change (Wise, Zhao, & Hausknecht, 2014).

The Principle of Customization

The principle of Customization emerges from the recognition that there are multiple, disparate, and equally valid needs and paths (and potentially endpoints) for different learning analytics users. Customization of learning analytics to meet these different needs can be thought of in two ways. The first approach is computationally driven and can be thought of as *adaptive learning analytics* (cf. Brusilovsky & Peylo, 2003). As this relates to the design of the learning analytics system rather than the learning analytics implementation, it is not addressed further here. A second approach to personalization is user-driven and can be thought of as *adaptable learning analytics* (cf. Brooks et al., 2014). In this case, the analytics interface allows for different kinds of uses by different individuals who determine themselves which analytics they will attend to and in what way. There is a danger, however, that users may be overwhelmed by the multitude of possible options without a clear basis on which to make choices. Thus implementation design needs to support user agency actively by guiding them in the process of effectively making decisions about how to use the learning analytics provided to meet their own needs and context.

LEARNING ANALYTICS IMPLICATION DESIGN FOR INSTRUCTORS

Instructors are a natural audience for learning analytics as they are often already engaged informally in the activity of examining student learning to inform their practice. Such teacher-inquiry has traditionally depended on qualitative methods of reflection using journals, interviews, peer-observation, student observations and examination of learning artifacts (Lytle & Cochran-Smith, 1990), though interest in the use of student data as evidence to inform this process has been increasing (Wasson, Hanson, & Mor, 2016). Analytics can support instructors in approaching this reflective cycle with more detail, using data as an aid in assessing the impact of teaching decisions on learning activity (Mor, Ferguson, & Wasson, 2015). Different bodies of literature have explored specific process of instructor use of analytics in relation to the practices of learning design, orchestration, and assessment.

One perspective focuses on the use of analytics to inform learning design. From this perspective, instructors document their pedagogical intentions through the design, which then provides the conceptual frame for asking questions and making sense of the information provided by the analytics (Dawson, Bakharia, Lockyer, & Heathcote, 2011). This can facilitate an understanding of the effects of a learning design (or specific instructional approach) on student activity and learning (Dietz-Uhler & Hurn, 2013), which can then feed back into improving the design (Persico & Pozzi, 2015; Mor et al., 2015). The process is a cyclical one in which the analytics make the learning processes undertaken by students visible (Martínez-Monés, Harrer, & Dimitriadis, 2011). A specific model for aligning learning analytics use with learning design was developed by Lockyer et al. (2013) who described how instructors can initially map the learning process supported by their design, pre-identify activity patterns that indicate successful (or unsuccessful) student engagement in the pedagogical design, and then use analytics to track learner progression towards the desired outcomes. An initial example of this cycle in action is given in Brooks et al. (2014) who look at instructors' modifications of their discussion forum practices based on sociograms created from students' speaking and listening activity. A similar cycle as engaged in by course designers of a MOOC is given in Roll, Harris, Paulin, MacFadyen, and Ni (2016). Lockyer et al.'s (2013) model represents a strong application of the principle of Coordination as it makes clear how the use of the analytics is integrally tied to the goals and expectations for learning. It also suggests ways analytics can be worked into an instructor's activity flow, for example by setting up checkpoints. The principle of Comparison is also attended to in the sense that the pre-identified activity patterns serve as an absolute reference frame to gauge progress towards a desired state. Additional comparisons – for example, setting incremental stages to target along the way or using prior activity to judge progress – could also be considered. As this use of learning analytics is directed globally at the effects of a learning design, attention to the principle of Customization is currently limited. However, thinking about how different learning designs might work differently and be more or less effective for different kinds of learners and learning contexts is an exciting area for future consideration.

An alternative conceptualization of instructors' analytics use shifts the focus from looking at data patterns for the course as a whole to looking at differences between students or student groups. From this perspective, the analytics are used in (relatively) real-time as a tool to monitor activity, support the diagnoses of situations needing attention, and prompt instructors to intervene when necessary. This can be thought of as a form of orchestration (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015) in which instructors use analytics to support their awareness of student activity and adapt their teaching to meet student needs (Feldon, 2007). To address the inherent challenges in doing this (Dyckhoff, Lukarov, Muslim, Chatti, & Schroeder, 2013), van Leeuwen (2015) proposes a two-part model of how instructors can work with analytics in this capacity. First, instructors use the analytics to monitor student activity, specifically noticing important differences across individuals or groups. This is supported by the capabilities of analytics to aggregate information for manageable presentation. Second, instructors use the information to inform their diagnosis of situations, individuals, or groups requiring attention. Working in the context of a learning analytics application for a computer-supported collaborative learning context, van Leeuwen (2015) found initial evidence to support the hypothesis that analytics use would increase both the specificity of instructor diagnoses and inform the actions that they took. This model represents a strong application of the principle of Customization as the goal of instructors' analytics use is individualized actions tailored to particular student or group needs. With respect to Comparison, in the original conceptualization there is strong reliance on the relative frame of peer activity, though the prior activity of a group or individual are also taken into account. The addition of an absolute standard with which to compare activity could also be considered. An area for future development is the Coordination of this kind of analytics use with the larger purpose and flow of the collaborative learning activity.

A final model for instructor use of learning analytics that has yet to be fully developed is as a tool for assessment. While there is a need for caution in such applications, there are exciting possibilities for using temporal analytics (which capture time-based characteristics of trace data) to move towards a new paradigm of assessment that replaces current point-in-time evaluations of learning *states* with dynamic evaluations of learning *progress* (Molenaar & Wise, 2016). Such an approach is grounded in Comparison with prior activity and offers opportunities for instructors to respond to individual and evolving learning needs. Using analytics collected during the normal course of learning processes to evaluate the development of student understanding in situ also presents an attractive opportunity for assessment that can both meet summative needs and serve formative purposes. However, the conceptual and logistical Coordination of how learning analytics are used for such assessment purposes is critical for adoption, given the importance of decisions often attached to assessment activities.

LEARNING ANALYTICS IMPLICATION DESIGN FOR STUDENTS

Students are an important audience for analytics use for several reasons. First, since student learning is the ultimate goal of educational systems, much of the data collected in learning analytics systems is information generated by or about students. From an ethical perspective, students have the right (and perhaps the responsibility) to review their own data (Pardo & Siemens, 2014; Slade & Prinsloo, 2013). Second, similar to instructors, students are also at the "front line" of learning and thus potentially well-equipped to bring local context to bear in interpreting analytics, as well as make immediate adjustments to their learning processes based on them. Different from instructors, however, students must negotiate between course-wide goals for learning and analytics use and their own personal objectives (Wise, 2014). This explicitly allows for Customization as it adds an additional personalized reference frame for Comparison.

Student use of analytics has been conceptualized primarily in terms of a reflective cycle in which students use their own analytic data to inform their individual learning processes. Drawing on the theories of Schön (1983) and Kolb (1984), Clow (2012) has put forward the general idea of analytics use as an element of reflective practice in which the information provides feedback that students can use to adjust or experiment with changes in their learning activities. The notion of students using analytics to act as "little experimenters" has also been discussed within the self-regulated learning literature (Winne, in press). Drawing on theories of metacognition, this field has a long history of studying and supporting the ways students monitor and take action on their learning as part of a self-regulative process (Zimmerman & Schunk, 2011; Schunk 2008; Boekaerts, Pintrich, & Zeidner, 2000). Students who adopt positive SRL strategies tend to have richer learning interactions and perform better in their studies (Zimmerman, 2008; Pintrich, 2004; Pardo, Han, & Ellis, 2016). While such efforts have traditionally been limited by the challenges and inaccuracies of human memory and recall (Winne, 2010; Azevedo, Moos, Johnson, & Chauncey, 2010), analytics offer the exciting potential to mirror a learner's activity back to them with greater ease and accuracy (Winne & Baker, 2013). From this perspective, learning analytics are conceived of as a way to cue students to effectively monitor and take action on their learning (Roll & Winne, 2015).

Expanding on these ideas, a more specific vision of student learning analytics use has been put forth by Wise and colleagues (Wise et al., 2016; Wise, 2014; Wise, Zhao, & Hausknecht, 2013; 2014). Their Student Tuning Model describes student's learning-analytics-informed reflective practice as grounded in the relationship between the learning activities and the learning analytics. Students work with this relationship continually as they engage in cycles of goal setting, action, reflection, and adjustment. To support this descriptive cycle of analytics use, Wise et al. (2016) have proposed and presented initial validation evidence for a pedagogical framework for designing learning analytics implementations for students. The Align Design framework utilizes elements of Coordination, Comparison, and Customization as described above with an emphasis on the interplay between agency and dialogue with the situation.

In addition to these overarching models of students' learning analytics use, there are other ongoing research efforts proposing targeted pedagogical frameworks for specific learning contexts and exploring particular aspects of how to design learning analytics implementations for students. Koh et al. (2016) have developed the Team and Self-Diagnostic Learning framework for analytics use in the context of collaborative inquiry with secondary students. This framework provides strong process-based Coordination by integrating instructor-guided use of teamwork competency analytics into students' experiential learning cycles. Attention to Comparison takes the form of contrasts of similarities and difference between self- and peer-ratings on six dimensions of teamwork.

Separately, Aguilar (2015) is conducting research at the intersection of the Customization and Comparison principles, examining whether students' mastery or performance orientation to learning can help determine when peer activity is a useful reference frame for evaluating learning analytics. Similarly, research into individual differences has shown that particular goal-orientations are associated with the use of different kinds of self-regulatory strategies generally (Shirazi, Gašević, & Hatala, 2015) and can specifically influence the interpretation and use of different learning analytics visualizations (Beheshitha, Hatala, Gašević, & Joksimović, 2016).

Such findings can have implications for system-driven adaptive analytics in terms of what measures with what references points are helpful (and ethical) to show to particular learners. For example, while the peer reference frame can be can be motivating in showing a student where they stand in relation to others in the class for some students (Beheshitha et al., 2016; Govaerts, et al., 2012), it can be distracting for others (Corrin & de Barba, 2015). Some students find it demotivating to find out they are doing substantially worse than their classmates (Wise, Hausknecht, & Zhao, 2014). Especially for students who are struggling, the ability to document improvement in comparison to their own prior activity may be more powerful than comparison to a distal class mean. In addition, there are questions of which portion(s) of a peer group are most appropriate for comparison in a given situation; for example, should students be shown data for the whole course, only students who are similar to them in some way, or the "top performers" (Beheshitha et al., 2016). The answer will depend on the kind of activity, relevant student characteristics, and the objective for analytics use.

Other researchers are probing more deeply into ways in which learning analytics implementations can be designed to support student Customization in terms of adaptable analytics implementations. For example, Santos, Govaerts, Verbert, and Duval (2012) describe a process in which students articulate individual goals and then track their progress. Ferguson, Buckingham Shum, and Deakin Crick (2011) have used blogs as a tool for creating individually owned reflective spaces in which students can work through the sense-making of the analytics. The need for students to have time to "digest" the meaning of the analytics before taking action is also supported by the findings of Koh et al. (2016), suggesting that appropriate pacing may be a critical aspect in the Coordination of reflective learning analytics use with the overarching learning activities. In contrast, Holman et al. (2015) found that for predictive analytics use focused on course progress, students tended to use the tools to make plans (and follow-through on these plans) mostly in short bursts just prior to major course deadlines.

While the models and research discussed above have primarily conceptualized student learning analytics use as an individual endeavor, there are also intriguing opportunities for students to work with analytics collectively. This follows the tradition of "group awareness" tools, which have been used to facilitate computer-supported collaborative work and learning (Buder, 2011; Janssen & Bodemer, 2013). In this case, the individuals in a group and the group collectively work with analytics to improve their joint learning process through socially shared regulation (Järvelä et al., 2015).

IMPLICATIONS FOR LEARNING ANALYTICS DESIGNERS AND RESEARCHERS

The above discussion has described three principles for designing learning analytics implementations and has presented current research and models of learning analytics use by instructors and students. This framework can also be used to discuss implications for learning analytics design and research more generally.

First, from a systems design perspective, we can anticipate and create features to support implementation possibilities. For example, a tool that allows instructors to associate particular analytics and course goals (and annotate these connections with examples of productive or unproductive patterns) would support the principle of Coordination. Similarly, creating tools that help students track and reflect on the changes in their analytics over time (for example by being able to adjust the time window of the analytics for both current and historical data) could support the principles of Customization. This latter point is of particular importance given the usefulness of prior activity as a reference frame for evaluating progress, but the predominance of analytic dashboards that only provide point-in-time "snapshots."

Second, from a research perspective, in addition to continued work to develop useful analytics systems, inquiry is also needed into how activity using such analytics is best motivated and mobilized, and the factors influencing this process. Practically, this suggests that laboratory studies, which ask people to perform specific tasks or determine particular information with learning analytics tools, can only contribute so much to predicting how instructors and students will work with analytics "in the wild." Thus field-testing new analytics in real educational contexts early on may prove particularly important in developing learning analytics systems and implementations that truly impact teaching and learning. One valuable approach to consider is Design-Based Intervention Research (Penuel, Fishman, Cheng, & Sabelli, 2011), which emphasizes multiple iterations of testing and (re)design of learning innovations in partnership with practitioners to support on-the-ground use and sustainability.

Finally, it is critical to consider the use of analytics as a radically new technology for instructors and students. Careful planning of how the analytics will be introduced, with appropriate up-front guidance, ongoing support, diverse examples, and time for instructors and students to figure out how to integrate this new form of feedback into their practice is needed to translate the promise of learning analytics into reality. Widespread adoption of learning analytics will not occur spontaneously, but initial reports from projects that have used implementation design to educate users and nurture their analytics use are very promising (Koh et al., 2016; Wise et al., 2016).

CONCLUSION

This chapter reflects the current state of the art of learning analytics implementation design. The principles of Coordination, Comparison, and Customization provide a lens to examine the different dimensions of design choice that can affect how analytics feedback is taken up and acted on in particular educational contexts. For instructors, models have been proposed for analytics use to examine and adjust course-wide learning designs as well as to investigate and respond to individual student activity patterns via orchestration. The use of learning analytics for assessment is a potentially exciting but undeveloped area for application. Student use currently takes the form of a reflective, self-regulative cycle, with attention given to particular ways to support this process. Further research into the impact of students' and instructors' individual differences on analytics use and the generation of designs to support their particular needs is a promising area for future work. The final message of this chapter is to emphasize that intentional implementation design is essential, not optional, for learning analytics adoption. If we wish to avoid the fate of too many promising technologies that never made a real impact on education, research into the interplay of human and technological elements influencing analytics use is a critical area for attention in the field moving forward.

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