

Advances in Analytics for Learning and Teaching

Olga Viberg
Åke Grönlund *Editors*

Practicable Learning Analytics

 Springer

Advances in Analytics for Learning and Teaching

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Practicable Learning Analytics

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Foreword to Practicable Learning Analytics

Concern with practice has been a part of the field of learning analytics since its inception. Going back to the call for the very first International Conference on Learning Analytics and Knowledge in 2011, a core vision for the community's formation was that “technical, pedagogical, and social domains must be brought into dialogue with each other to ensure that interventions and organizational systems serve the needs of all stakeholders.” Yet just over ten years later, the vast majority of learning analytics systems are developed without the deep involvement of those they seek to serve, and cases of widespread analytics adoption are few and far-between. This is worrisome—tools that do not productively fit into and improve the ways that teachers, learners and other stakeholders go about the doing the work of education will inevitably end up gathering dust on a shelf, as ample examples of educational technologies from the last century attest. Thus, the question of whether learning analytics fulfills the visions many have for it as a technology that ultimately has a significant and lasting impact on teaching and learning is one which remains very much open.

It is in this context that a book such as *Practicable Learning Analytics* is very much a timely and needed contribution to the field. The notion of learning analytics that are “practicable,” that is able to become a successful part of practice, is a powerful one that shifts our perspective on learning analytics creation and implementation: from that of the “designing of” a tool to that of “designing for” a system. Put in the language of the *Information System Artefact* concepts introduced in Chap. 1, we are pressed to center the question of how the “social artefact” of people acting and interacting in the service of learning will be affected by changes to the “technical” and “informational” artefacts introduced by analytics. This is a critical difference that inverts the core anticipatory question of design from that of “how do we expect people to *work with this tool?*” to “how do we expect the tool to alter how people *go about their work?*”

This both encompasses and goes beyond a recent shift in the field towards “human-centered” learning analytics. Similarities include sincere attention to the perspective, needs and agency of key stakeholders and what they are trying to accomplish, particularly by involving them in the process of design. For example,

Chap. 5 dives deeply into how participatory design methods using jointly created persona profiles and learner journeys can aid in the creation of analytics that both inspire trust and fit into the existing routines of student activity. Considering how learning analytics will become a part of (and also modify) existing practices is certainly a key element for the practicability of learning analytics as also seen in Chap. 7 for the case of regulating collaborative learning practices and Chap. 9 for the generation of useful analytic data about “learner-sourced” educational resources.

However, practicability and the contributions of the book also go beyond a consideration of particular humans and their individual activities to consider the larger *systems of activity* of which analytics will become part. This includes critical elements such as infrastructure, policy, division of labor and goals, which may also differ and conflict across the system. Such multifaceted issues are engaged with across the chapters of the book on multiple levels. For example, Chap. 6 describes the utility of a model for identifying influential actors, desired behaviors and change strategies (among other things) as part of early-stage adoption in higher education in Latin America when familiarity with analytics is relatively low. Similarly, Chap. 4 describes not only the design of a dashboard to support the (existing) practice of conversations between academic advisors and students, but also the importance of recognizing and managing the different goals and expectations for such a tool by advisors (who wanted to better understand students) and administrators (who were focused on reducing dropout). The fit of analytics into existing institutional technology practices as planning for long-term viability (both technological and as part of system practices) were also emphasized here as they were in Chap. 2 which used the powerful metaphor of the different “rooms” in which institutional conversations need to take place in order for learning analytics to successfully integrate at scale. Considering the need to communicate in different ways with senior leadership, academics, technologists and students is an important reminder that even while a systems perspective requires constant consideration of interconnected elements, it does not require uniformity in language or perspective. In fact, from the perspective of Engeström’s Activity Theory (Engeström, 1987, 1999), it is productive tensions within and across elements that keep a system dynamic. Learning to recognize and navigate such tensions is as much an important part of learning analytics work as the technical components. It is also one which merits increased attention in the development of effective learning analytics practitioners as highlighted in the review of current learning analytics education efforts in Chap. 8.

While the notion of practicable learning analytics has much to offer the field, it also raises important questions. One particularly thorny one is the question of generalizability, an important component of analytic promise. Put in simple terms, if we need to understand an existing system to anticipate (and productively design for) the ways in which analytics will affect activity within, we may lose much of the benefit of scale. A potential solution, discussed in several chapters and focused on in Chap. 2, is the notion of adaptation (by designers) or customization (by users) of tools to meet the needs of targeted local contexts, while at the same time keeping in mind the potential for the tools to shift practice (for example, enhancing attention to

learning design through the introduction of learning analytics). In considering practices and needs within different systems, there are many components to take into account; in addition to those mentioned already, questions of values are of particular importance. These may relate to the purposes for analytics use, but also to questions of ethics and privacy, which may vary across and within institutions and countries. Reviewing central concepts of the learning analytics policy frameworks across selected institutions in the UK, Canada and Australia, Chap. 11 discusses the different ways attention to questions of transparency, access, and bias manifests. Considering these issues as well as those of trust, openness and autonomy, Chap. 10 focuses explicitly on the cultural dimensions of differences in orientation. It introduces the notion of values-sensitive design from HCI as a way to move towards culturally sensitive analytics, asking important questions regarding who makes decisions with and about learning analytics. Expanding these ideas beyond the design of the tool, we can also come full circle to consider the ways values operate within and across the different elements of the system as a whole to make different kinds of uses of learning analytics practicable or not.

I was recently asked to deliver a keynote at a learning analytics event whose theme was “Developing a Culture of Learning Analytics.” For me, this focus immediately evoked the notion of Practicable Learning Analytics in that a true culture of learning analytics is more than just a word in which learning analytics are commonly used, but a soup-to-nuts vision for one in which learning analytics are continuously designed, adopted, evaluated and revised in relation to their ability to productively support students, teachers, advisors and/or other educators in their existing and aspirational real-world learning practices. Importantly, as the chapters in this book illustrate, there will never be just one omnibus learning analytics culture (singular) but necessarily a variety of learning analytics cultures (plural). Across these chapters, three key themes related to the support of such multiple cultures emerge to keep in mind: first, how to initiate and maintain necessary conversations with different kinds of stakeholders across the system; second, the potential and challenges of customization to help meet multiple needs; and finally, the anticipation of evolution in tools, practices and use as cultures of analytics evolve over time.

In conclusion, I recommend this book to all designers, students and educators of learning analytics who want their work to have impact in the real world (hoping that this refers *all* designers, students and educators of learning analytics). The diverse aspects of making learning analytics practicable addressed across the rich experiences described the chapters offer much to expand the thinking of even the most experienced learning analytics designer among us and help us take the potential of learning analytics from promise to reality.

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Alyssa Wise

References

- Engeström, Y. (1987). *Learning by expanding: An activity-theoretical approach to developmental research*. Orienta-Konsultit.
- Engeström, Y. (1999). Innovative learning in work teams: analysing cycles of knowledge creation in practice. In: Y. Engeström et al. (Eds.) *Perspectives on activity theory* (pp. 377–406). Cambridge University Press.

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Abbreviations

| | |
|--------|---|
| AI | Artificial Intelligence |
| BDP | Balanced Design Planning |
| DBR | Design-Based Research |
| CIC | Connected Intelligent Centre |
| CL | Collaborative Learning |
| CPS | Collaborative Problem Solving |
| EDA | Electrodermal Activity |
| EDM | Educational Data Mining |
| HCD | Human-Centered Design |
| HCI | Human-Computer Interaction |
| HCLA | Human-Centered Learning Analytics |
| HE | Higher Education |
| ISA | Information Systems Artefact |
| JCC | Joined Creative Classroom |
| LA | Learning Analytics |
| LAK | Learning Analytics and Knowledge |
| LD | Learning Design |
| LIME | Local Interpretable Model-Agnostic Explanations |
| LMS | Learning Management System |
| Local | Local Rule-Based Explanations |
| LISSA | Learning Dashboard for Insights and Support During Study Advice |
| LO | Learning Objectives |
| LXD | Learning Experience Design |
| ML | Machine Learning |
| MMLA | Multimodal Learning Analytics |
| MOOCS | Massive Online Open Courses |
| OULDI | Open University Learning Design Initiative |
| ROMA | Rapid Outcome Mapping Approach |
| SHEILA | Supporting Higher Education to Integrate Learning Analytics |
| SoLAR | Society of Learning Analytics Research |
| SSRL | Socially Shared Regulation of Learning |

| | |
|-----|----------------------------------|
| S3 | Student Success System |
| SRL | Self-Regulated Learning |
| TEL | Technology-Enhanced Learning |
| TLA | Teaching and Learning Activities |
| UA | Usability Engineering |
| XAI | Explainable AI |

Chapter 1

Introducing Practicable Learning Analytics



Åke Grönlund and Olga Viberg

1.1 Introduction

This book is about *practicable learning analytics*. So, let us begin by defining what we mean by *learning analytics* and by *practicable*. Learning analytics has over the last 10 years become an established field of inquiry and a growing community of researchers and practitioners (Lang et al., 2022). It has been suggested as one of the learning technologies and practices that will significantly impact the future of teaching and learning (Pelletier et al., 2021). It is argued to be able to improve learning practice by transforming the ways we support learning and teaching (Viberg et al., 2018).

Learning analytics has been defined in several ways (Draschler & Kalz, 2016; Rubel & Jones, 2016; Xing et al., 2015). A widely employed and accepted definition explains it as the “measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs” (Long & Siemens, 2011, p. 34).

In order to recognise the complex nature of the learning analytics field, its related opportunities and corresponding challenges, researchers have stressed a need to further define and clarify what “kinds of improvement [in education] we seek to make, the most productive paths towards them, and to start to generate compelling evidence of the positive changes possible through learning analytics” (Lang et al., 2022, p. 14). Such evidence has so far been scarce and, to the extent it exists, it is

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often limited in scale (e.g., Ferguson & Clow, 2017; Ifenthaler et al., 2021; Gašević et al., 2022). What does exist is predominantly found in higher education settings (e.g., Viberg et al., 2018; Wong & Li, 2020; Ifenthaler et al., 2021); in K-12 settings, learning analytics research efforts have hitherto been limited (see e.g., De Sousa et al., 2021). If learning analytics can deliver on its promises, K-12 is arguably an even more important practice to improve as it concerns many more students and is more critical to society as it serves to educate the whole population, which makes it an even more complex field of activity.

In all educational contexts, there is a need to deliver on the promises of learning analytics and translate the unrealised potential into practice for improved learning at scale. But clearly learning analytics cannot be simplistically “put into practice”, it has to be adopted into practice by practitioners who see a need for it and practical ways of using it. It has to be practicable.

Practicable suggests that something is “able to be done” or “put into action” or practised “successfully” (Cambridge Dictionary, 2022; Oxford Learner’s Dictionary, 2022). This raises some questions: What exactly is that ‘something’ in learning analytics? Who is going to put it into practice? What practices are learning analytics aiming to improve? and How can we distinguish between what is more or less practicable? Would not it be good to have a theory for that, rather than just focusing on different aspects of learning analytics examinations, such as self-regulated learning (e.g., Montgomery et al., 2019; Viberg et al., 2020), collaborative learning (e.g., Wise et al., 2021a, b) or social learning (e.g., Kaliisa et al., 2022). While these diverse learning analytics efforts are both interesting and meaningful to support, it is worthwhile to look at learning and teaching in a more systemic way, looking beyond isolated activities and considering them as a whole system orchestrated for students learning. Education is composed of many activities conducted by both students and teachers, and affected by environmental factors. The latter includes many factors ranging from physical, like light and noise in the classroom, to social, like class sizes and composition and attitudes to learning in the home. Changes in one of those activities or factors may affect the others and may hence have consequences for the learning outcomes. It is not necessarily the case that focusing specifically on improving one factor leads to overall improvement of the system as a whole.

For example, Zhu, analysing data from the Programme for International Student Assessment (PISA), showed that reading literacy was significantly more important than mathematics for achievements in science (Zhu, 2022), it was also directly influential on their mathematics achievements. Similarly, in a quasi-experimental study, Agélli Genlott and Grönlund (2016) introduced an ICT-supported method for improving literacy training in primary school and found that not only students’ literacy achievements but also those in mathematics improved significantly, as measured by the national standard tests.

Such findings suggest that there are complex relations involved in learning; if you want to improve students’ skills in mathematics and science, improving literacy training may be a good way to go. It certainly appears to be a bad idea to reduce

literacy training to increase the time spent on mathematics training. So let us consider education practices from a systemic perspective.

1.2 A Systemic Perspective on Education Practices

Making the use of learning analytics come into use in everyday teaching and learning activities at scale requires the tools and methods use to fit with the educational environments in which they are to be used. However, educational systems and activities are manifold and diverse, and even a brief analysis shows a great variety of situations and undertakings, as well as several stakeholders who may have different interests in learning analytics.

Stakeholders Students and teachers are the frequently focused stakeholders in the learning analytics literature (e.g., Draschler & Greller, 2012; Gašević et al., 2022; Gray et al., 2022), but educational leaders and school administrations are also involved and, in particular for younger students, parents have interest and take some part. These stakeholders play different roles and do not necessarily share the same view of what should be done in an educational institution and how to do that. While teachers and students take the keenest interest in the actual learning and teaching activities, parents, institutional leaders and school administrations are typically more interested in the results, often in the form of grades. Stakeholders can also include educational technology companies (e.g., learning management systems providers) bringing a commercial interest, and also researchers acting in the field. In sum, there are many stakeholders who may have quite different needs and interests in learning analytics (e.g., Sun et al., 2019), and this needs to be carefully considered when planning any learning analytics undertaking. It is easy to see that several conflicts between the interests of different stakeholders may come up. For example, Wise et al. (2021b) note that student and teacher stakeholders often fear that learning analytics systems are less about improving education and more about serving surveillance needs of the administration. They use the concept of “subversive learning analytics” to discuss the need to take a critical stance in order to disclose hidden assumptions built into technology designs.

Situations Teaching and learning situations are quite different in school (especially primary and secondary) than at the university. Furthermore, learning frequently takes place with no teacher present and outside of school or scheduled classes at the university. The amount of individual student work and the responsibility of students to study independently increases as students get older, but it is also influenced by the number of teachers available, goals of educational programs, pedagogical approaches as well as educational and cultural contexts. Different study subjects require or entail certain activities, which may involve practical operations, movement, communication, testing, group work, and more. Some involve learning specific concepts, some involve understanding of systems, structures, logical reasoning,

causes and effects in physical, social, or psychological matters, or all of these in combination.

In an average week, a student meets several teachers, several topics, and several situations. But common for them all is that there is some *information* to be handled and this takes place in a *social context*. As for the information, it is not only a content, it also has a form. It is typically written, audio or visual, but it may also be haptic or even tacit, such as when for example social behavioural norms are communicated by actions or non-actions. In an educational context, information must be presented in a form that is conducive to learning.

Introducing new technology, such as a novel learning analytics system, into an educational setting means changing both the situations and the information, and one cannot be changed without changing the other. For example, changing from reading a textbook to listening to the teacher means you have to stop listening to music on your headphones. This means that technology can also be seen as an actor in the social situation as it affects the conditions for student learning in several ways: in some situations, leading to improved learning but in others resulting in negative learning outcomes. That is, we cannot expect any new learning analytics tool introduced in a selected educational context to influence student learning directly and positively (as anticipated by designers); it changes the conditions in which learning activities occur, but the actual effect depends both on the technology and the situation, and it can be positive or negative. Often it is both; some of the anticipated positive effects may occur but also some “unintended consequence” that may be negative. The better we understand the situation before we intervene, the more likely we will design technology that has positive effects and no, or minimal, negative ones.

For at least fifty years, the discipline of information systems has been concerned with the introduction of information technology into people’s work situations, that is, changing the social and informational situation of work. Pioneering in this regard was the Tavistock Institute in London where the concept of sociotechnical systems was coined (Emery & Trist, 1960). Sociotechnical systems analysis and design was developed in the field of information systems design in the 1970s and onwards, pioneered by the Manchester Business School where Enid Mumford was a portal figure in the field of information systems, for example by developing the human-centred systems design method ETHICS (Effective Technical and Human Implementation of Computer Systems) (Mumford & Weir, 1979).

The sociotechnical approach has since seen many developments, many new models and methods for analysis and design. The areas of work affected by digitalisation of tools and processes have multiplied – and education is among the most recent to be explored, decades after office work. An increasing number of theories have also come to use for analysing the relations between people and technology – and between *people*, *organisations* and *technology*. As an example, Wise et al. (2021a, b) discuss critical learning analysis, critical race theory, speculative design and – still going strong! – sociotechnical systems.

1.3 The “Information System Artefact” in Learning Analytics

The research field of Learning Analytics is situated in the intersection of Learning, Analytics and Human-Centred Design (SOLAR 2021). “Learning” includes (at least) educational research, learning and assessment sciences, educational technology, “analytics” comprises, e.g., statistics, visualisation, computer/data sciences, artificial intelligence (but also qualitative analyses, such as critical analysis), and “human-centred design” is concerned with issues like usability, participatory design, sociotechnical systems thinking (SOLAR 2021). All these aspects are critical to successful implementation of learning analytics and require a carefully considered, approach to not only measure, but to better explain the targeted learning or teaching activities or processes.

The disciplines of informatics (often named information systems) and computer science both share the interest in information technology artefacts, but informatics is distinguished by its focus on the user, which is in line with recent efforts on *human-centred* learning analytics (e.g., Buckingham Shum et al., 2019; Ochoa & Wise, 2021). Who are the users of these technologies? What do they do? and How can technology help them do better? The object of study is people and technology *together*, and the concept of “information system” is typically defined as “a formal, sociotechnical, organizational system designed to collect, process, store, and distribute information” (Piccoli & Pigni, 2018, p. 28).

A theoretical expression of that interest in users and use contexts is the notion of the *Information System Artefact* (ISA), as distinct from the information technology artefact (Lee et al., 2015). The ISA is “a system, itself comprising of three subsystems that are (1) a *technology* artefact, (2) an *information* artefact and (3) a *social* artefact, where the whole (the ISA) is greater than the sum of its parts (the three constituent artefacts as subsystems), where the information technology artefact (if one exists at all) does not necessarily predominate in considerations of design and where the ISA itself is something that people create” (i.e. an ‘artefact’; Lee et al., 2015, p. 6). The three sub-artefacts are interrelated and interdependent, which means that ‘improving’ one of the artefacts (in the literature, typically the technical, e.g., a learning analytics service) may in fact lead to a deterioration of the ISA. What is considered an improvement in any subsystem is only that which contributes to improving the whole, the ISA.

To make a LA system ‘*practicable*’ in our terms means understanding how it enhances the ISA as a whole in the targeted educational setting. The ISA should be understood as an object to be designed. Creating and implementing a learning analytics system means designing a technical, a social and an information artefact in such a way that they interact well to improve the overall ISA, ultimately leading to student improved learning. This argument echoes the earlier call for a more systemic approach to learning analytics (Ferguson et al., 2014; Gašević et al., 2019).

Lee et al. (2015) define the components of the ISA, the three sub-artefacts, in the following way:

The *technology artefact*: “a human-created tool whose raison d’être is to be used to solve a problem, achieve a goal or serve a purpose that is human defined, human perceived or human felt” (p. 8). In the learning analytics setting, it could be different tools such as learning dashboards (see e.g., Susnjak et al., 2022) or other tools aimed at, for example, supporting students’ self-regulated learning (for overview, see Perez Alvarez et al., 2022) or formative feedback on academic writing (e.g., Knight et al., 2020) or collaborative peer feedback (e.g., Er et al., 2021).

The *information artefact*: “an instantiation of information, where the instantiation occurs through a human act either directly (as could happen through a person’s verbal or written statement of a fact) or indirectly (as could happen through a person’s running of a computer program to produce a quarterly report)” (p. 8). The role of the *information artefact* in an educational setting can be to “form meaning”, i.e., learn something, but it can also be other things, such as process information (like a calculator) or serve as a structure for information exchange (e.g., the alphabet).

The *information artefact*, hence, includes all the information that is present in a learning situation (in the case of learning analytics). Some of this information is subject to learning (the subject content), some is contextual (e.g., what concerns work methods). Introducing a technology artefact in an existing learning situation changes the information artefact inasmuch as some new information may be added and some already existing information may appear in a different form (e.g., digital instead of physical or presented in a different digital format) or become available to students by different methods. This means any new learning analytics tool (a technology artefact) will in some way affect the information artefact of an educational context.

The *social artefact* “consists of, or incorporates, relationships or interactions between or among individuals through which an individual attempts to solve one of his or her problems, achieve one of his or her goals or serve one of his or her purposes” (p. 9). *Social* here means not just specific situations, like when a number of people meet and communicate, but also established, persistent relations such as institutions, roles, cultures, laws, policies and kinship.

In a simple way, the social artefact can be thought of as ‘the classroom’. In a physical classroom, there are people with relations: professional and social. Professional relations concern the formal and technical part of teacher-student interaction (the teaching and learning activities), which is partly a function of the way it is organised as concerns, rules of conduct, time allocation, physical environment, class size, examination forms, and more. Social relations concern students’ relations to each other, but also students’ relation to schoolwork – which may differ from very positive and uncomplicated to very negative and complicated – and the nature of the student-teacher communication, which is very much dependent on the personalities of the people involved.

The *social artefact* is much affected by changes in both the technology and the information ones. For example, when a new technology artefact is introduced in the