Advances in Analytics for Learning and Teaching

Olga Viberg
Åke Grönlund *Editors*

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 additional 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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Contents

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 insomuch 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 classroom (the social artefact), it may mean that information that previously was physically available (e.g., a paper textbook or a teacher writing on a whiteboard) becomes part of the *technology* artefact and accessed and manipulable in new ways, the teacher-student communication changes. Teachers may have to spend time explaining to students how to handle the new tool, or students have to explain to teachers how they use them. Teachers may be less able to inspect students' work as it no longer is visible in the same way as previously when they could overview the work of an entire class in a moment. A 'social inspection' available by physical means – looking around in the classroom and then observing both individual work and social contacts – is to some extent replaced by an individual one available only through technical means (to the extent that the learning analytics application allows for that). Taken together, this means a change in the *social artefact* reducing the amount of physical communication and increasing the amount of technology-mediated communication. To what extent the quality of the social artefact is increased or reduced is subject to analysis, which is often not straight-forward.

Using the ISA model, different stakeholders' views of, and relation to, learning analytics systems, the information they use and produce, and the role they could play in teaching and learning environments can be more clearly identified and analysed. Teaching and learning are complex phenomena taking place in (different) social contexts, and the ISA model provides an analytical framework that includes those contexts.

1.4 Overview of the Chapters

This book includes ten chapters (except this introductory chapter) that illustrate the examples and aspects of the *practicable* learning analytics efforts and related opportunities and challenges across three continents. Most concern higher education contexts. Whereas the first five chapters explicitly demonstrate institutional efforts to put learning analytics into practice at scale, the other five illustrate relevant efforts focusing on various aspects that are important to putting learning analytics into teaching and learning practice effectively.

In Chap. 2, Buckingham Shum (this volume) presents and critically reflects on the efforts of an Australian public university to design, pilot and evaluate learning analytics tools over the last decade. These efforts are summarised as conversations in the *Boardroom*, the *Staff Room*, the *Server Room* and the *Classroom*, reflecting the different levels of influence, partnership and adaptation necessary to introduce and sustain novel technologies in the complex system that constitutes any educational institution.

In Chap. 3, Rienties et al. (this volume) demonstrate how the (UK) Open University's Learning Design Initiative (OULDI) has been adopted and refined in a range of institutions to fit local and specific needs across three European projects, involving practitioners from nine countries. This chapter stresses that applying and translating the OULDI and learning analytics in other institutions and borders "is not a merely copy-paste job" since it requires a number of adaptations at different implementation levels, highlighting the importance of considering the targeted context. These required adaptations have been 'translated' into and presented as the Balanced Design Planning approach in the context of The University of Zagreb (Croatia).

In Chap. 4, De Laet (this volume) illustrates two cases of learning analytics implementations at the institutional level in the context of Belgian higher education. The first case reflects an institutional path of bringing learning analytics to advising practice, and the second one presents the ongoing institutional efforts of bringing predictive analytics to advising practice, an approach building on explainable artificial intelligence to uncover the existing black-box predictions.

Chapter 5 presents a project of "Learning Analytics – Students in Focus" in the context of another European university, TU Graz University of Technology. Through the lens of the human-centred learning analytics approach, Barreiros et al. (this volume) illustrate the iterative design, analysis, implementation and evaluation processes of the three learning analytics tools (i.e., the planner, the activity graph, and the learning diary), all contained in the student-facing dashboard.

In Chap. 6, Hilliger and Perez Sanagustín (this volume) introduce the LALA CANVAS: a conceptual model to support a participatory approach to learning analytics adoption in higher education. The model has been employed across four Latin American universities affiliated with the LALA (Building Capacity to Use Learning Analytics to Improve Higher Education in Latin America) project. The LALA CANVAS model is argued to be a useful model to formulate change strategies in higher education settings where the adoption of learning analytics is still at an early stage.

In Chap. 7, Järvelä et al. (this volume) present their recent empirical progress on metacognitive awareness and participation in cognitive and socio-emotional interaction to support the adaptive collaborative learning process. In particular, the authors present how learning process data and multimodal learning analytics can be used to uncover the regulation in computer-supported collaborative learning settings. They also provide a set of practical implications to assist students in collaborative learning activities.

In Chap. 8, Kizilcec and Davis (this volume) introduce the current state of learning analytics education across the globe. This chapter contributes to practicable learning analytics by providing evidence on the status quo of teaching and learning analytics with a comprehensive review of current learning analytics programs, topics and pedagogies focused. This is followed by an in-depth case study of a learning analytics course offered to the students at Cornell University. Finally, a set of actionable guidelines for the community to consider when designing learning analytics courses is offered.

In Chap. 9, Glassey and Bälter (this volume) present novel student data that learningsourcing produced. The aim is to marry learnersourcing efforts with learning analytics in terms of the types of novel learning data that is produced. The chapter provides a background to the emergence of learnersourcing as a topic, a taxonomy of the types of learnersourcing data and their supporting systems that increasingly make learnersourcing practicable for learning analytics. They also discuss challenges for using such data for learning analytics, for example as concerns data quality.

In Chap. 10, Viberg et al. (this volume) argue for the importance of addressing cultural values when designing and implementing learning analytics services across countries. Viewing culture from a value-sensitive perspective, this chapter exemplifies two selected values (privacy and autonomy) that might play an important role in the design of learning analytics systems and discusses opportunities for culture- and value-sensitive design methods that can guide the design of culturally aware learning analytics systems. A set of design implications for culturally aware and value-sensitive learning analytics services is offered at the end.

Finally, in Chap. 11, Mavroudi (this volume) reflects on the challenges associated with the ethical use of learning analytics in higher education, and how different selected policy frameworks address these challenges. It concludes with a list of practical recommendations on how to counteract specific challenges that might originate in the nature of learning analytics.

1.5 The Chapters in Context

Looking at the chapters in the book from the perspective of the ISA model, we find that most of them concern changes in the social artefact. In plain words that means changes in the way education is conducted. Education is somebody's work – teachers and students. Changing somebody's work from the outside – such as when introducing a learning analytics tool or system – will inevitably meet resistance unless it is clear to the people working in education that there is not something negative in it for them. The starting point is often a suspicion that there is – most professions tend to believe that they are the ones who best understand how to do their job, so if someone from outside demands a change professionals tend to suspect that there is another agenda at play.

For changes to be positively received, there should also be something *positive* in it for them. Even if positive effects for teachers and students can be expected they can be very hard to argue in a convincing way as they may be difficult to measure and as they often appear later while there is always more work upfront when new systems are introduced.

The changes presented in the chapters in this book always concern the *social artefact*, changes in teachers' and students' daily work environment. Sometimes those changes are effects of changes in the other artefacts, the *technical* or the *information*al. Other times, changes in the social artefact motivates changes in one or both of the others. In all cases, changes in one artefact entails changes in another, and these changes are not always foreseen or planned for. In plain words, intended changes often lead to unintended consequences.

In the highly pragmatic Chap. 2, Buckingham Shum (this volume) describes the entire setting in which learning analytics is to be implemented in terms of different "rooms". These rooms, which contain different stakeholders correspond quite directly to the different artefacts within ISA, and the chapter clearly describes the differences, and potential conflicts, between the different rooms. The *Staff Room*, the *Classroom*, and the *Boardroom* concern the *social* and *information* artefacts and focus on the required engagement of the different stakeholders involved: the university senior leadership, tutors, academics, students and teachers with learning analytics. But the *social* artefacts in the different rooms are different, representing different stakeholders' views and needs. In the *Staff Room* and the *Classroom*, there are teachers who are engaged in engaging with students and their work, and with the knowledge content of their courses, and who want to have information that can help them with that. In the *Boardroom*, university leadership is working in a business environment where the interest is in information about performance on university strategic priorities and how to improve return on investment in production. The learning analytics entrepreneur must engage both these audiences, but the way to do it differs as each room has different requirements on the information artefact. Information about teaching and learning, pedagogical issues and students' learning processes, is of interest for teachers, but in the Boardroom, there are rather requirements for information about production costs and results, including, for example, process effectiveness and efficiency, and performance of teachers. Not only is such information not interesting to teachers, it may even be discouraging to find that their own performance is monitored through the new system. The *Server Room* concerns the engagement with the information technology services, that is, the *technology artefact*, which is also critical to the success of any learning analytics implementation. Here, one important interest is how a new learning analytics system fits in with the existing ecosystem of applications which it needs to be able to interact with. This is not just a technical issue, the degree of integration among technical systems directly affects students' and teachers' work in the classroom.

Chapter 3, in presenting the new approach to learning analytics to fit local institutional needs across several European institutions, stresses the importance of the *information* and *social* artefacts but also the situational nature of them. Both the information handling and the social setup in which the system was to be used were areas where most adaptations to the system had to be made to fit the way education and administration were organised and conducted in different places due to regulation and practices, and at both national and local (university) level. These regulations were implemented in work instructions and practices of administrators, managers, and professionals, and in technical systems, which together formed a very firm social infrastructure to which any new work process must adapt. While there was less adaptation needed for the *technology* artefact in the case presented, this, too, needed concern as there has to be a sufficiently mature technical infrastructure in an organisation to be able to implement any learning analytics system.

Chapter 4 reflects on the interrelations between the three ISA sub-artefacts when presenting the scale-up process of the advising dashboard. The impetus to change came from an improved *technology* artefact aimed to improve the *information* artefact, that is, lead to better information handling and hence more effective work processes, specifically by supporting the dialogue between academic advisors and students. The change process involved several challenges related to the *social artefact*, including "overcoming resistance to change, alignment with educational values of the higher education institute, and tailoring to the particular context". Interestingly – and in contrast to similar efforts previously reported in the literature – the project was successful in terms of improving the *social artefact* – it resulted in the academic advisors (the key system users) feeling that the system made them better equipped to conduct a constructive and "more personal" dialogue with students. The author attributes this success to two main factors. First, the system did not include any prescriptive or predictive components, which are often found to be sources of resistance because they interfere uninvitedly in people's work (negatively affect the social artefact, in terms of ISA). Second, the implementation project took a bottom-up approach with the goal of supporting the advising dialogue and the professionals were included in an iterative user-centred design process, hence giving them an element of ownership and control of the new system.

Chapter 5 discusses a human-centred approach to LA design, which means the point of departure is the *social artefact*; the aim of a human-centred approach is to design work processes, work organisation, and technical systems to fit people. The chapter describes a project where use cases were first constructed. This was done by defining students' personas and descriptions of several scenarios illustrating when and with what intent the students may use the learning analytics dashboard to acquire or develop self-regulated skills, and how they might act to achieve a goal using the dashboard. Based on a selection of these scenarios, the project went on to produce design solutions, which were then moved forward to prototypes for testing with the intended users. In terms of the ISA, this means designing the entire ISA artefact using the *social artefact* (the scenarios) as the reference and as a test for the quality of the other two sub-artefacts. The prototypes represent the information and the technology artefacts. They were based on the scenarios; the *information artefact* concerned selecting which information to include and how to organise it to meet user needs, and the *technology artefact* concerned implementing the user interface to that information in such a way that it provides adequate support to their use processes. This shows a mutual dependence among the sub-artefacts. The social artefact informed the design of the information and technology artefacts, but the latter two also informed the design of the social artefact; during the design process, the prototypes were used to make the scenarios more concrete to users.

Similar to the previous chapter, Chap. 6 also starts from an interest in the *social artefact.* The contribution here is a conceptual model to support a participatory approach to learning analytics adoption in higher education; that is, a way to understand the social environment in which learning analytics is to work by means of direct user participation. The challenge is to discuss learning analytics at an early stage of development, which means it is still a rather hypothetical concept to participants as there is little in the form of examples of proven practice to guide prospective users' expectations. The method for discussion is group discussions, and the aim is to understand what needs there might be in educational practice that learning analytics could draw upon so as to be useful to practitioners. The model proposed and tested is built on factors known to be important for successful implementation:

political context, influential actors, desired behaviours, internal capabilities, change strategy, and indicators and instruments for assessment and evaluations.

In Chap. 7, again the *social artefact* is in focus, this time in a basic research perspective. The study studies group collaboration with the aim to be able to support its regulation. Effective collaborative learning requires group members to ensure that they work toward the shared goals and in order to be able to regulate their work they need to reveal to each other when they become aware that their collaboration is not heading toward the shared goals. This regulation takes place not only by using words but also by social, visual, cues of different kinds. The research studies multimodal data from group processes to identify “socially shared regulation episodes” (Järvelä et al., this volume).

Chapter 8 notes that higher education in learning analytics is conducted in different schools including not only Education but also Computer Science, Information Science and Media Studies. This means that both students and teachers come from a wide variety of disciplinary backgrounds, and many will not have a background in educational environments. The authors caution against overly focusing on numbers and – in the spirit of ISA, if not in the words – encourages educators to not forget the educational (social) environments where learning analytics are to be used (that is, the social artefact): “Before students are asked to conduct any analyses or learn a new programming language for data processing, it is critical that they first develop a strong foundational understanding of the field” (Kizilcec & Davis, this volume). This understanding will help them select what (educational) problems to engage with.

Chapter 9 concerns “learnersourcing”, where the basic idea is to have students do part of the grading or each other’s work by means of a (teacher-organised) peer-review process. This constitutes a major change in the way education is set up, that is the *social artefact*. It means the students must, to some part, assume a role as evaluator, which is quite contrary to the traditional role where they (individually or in cooperation) submit work for evaluation to another stakeholder in the setting, the teachers. It also means the teachers back off a little from the evaluation process by delegating parts of it to students. The main driver behind the change is to save teachers’ time by letting students do some of the information processing required for assessment of student work. In terms of the ISA, this means rearranging the *information artefacts*, and this change has considerable effects on the social artefact. This change redistributes some workload/information processing, but also changes the roles of stakeholders. It forces students to view their assignments from the perspective of teachers and of the stated quality criteria. It also changes the role of the teacher who becomes less of a direct actor and more of a “learning manager” overviewing a learning system (of students working in a digital tool) and intervening only as necessary.

Chapter 10 discusses how cultural values can be critical to learning analytics use, and how to make learning analytics design and related examinations “culturally aware” and “value-sensitive”. While culture is a concept that eludes strict definition, there are several cultural values that may strongly influence the social environment (the *social artefact*) that can be more clearly defined and that are valued differently in different countries. The chapter discusses two out of a set of such culturally significant values – privacy and autonomy – and discusses how design methods can take values into consideration.

Chapter 11 seeks to contribute to the discussion on the ethical usage (e.g., as concerns transparency, privacy, access) of learning analytics in higher education by examining the main theoretical concepts in the field against respective policies or codes of LA ethics at several selected universities in three countries.

This discussion directly concerns the *information* and the *technology artefacts* (how data about individuals is handled in a digital environment) but it more fundamentally concerns the *social artefact* as ethics is basically a social contract. The key to using data on individuals is consent by the individuals themselves. The legal regulation provides a – very strict – framework, but as many situations require data that is more or less personal and sensitive, consent is the method used to be able to retrieve and manipulate such data. In online shopping and social media, explicit consent is needed – "I agree to allow cookies" – but in education, there is a social contract between teachers and students that teachers can use some student data for the purpose of being able to teach them. Some of that data may be sensitive, like students' medical diagnoses and other personal characteristics, personal background, and views, which may affect learning and require special teaching methods. The condition to use such data is discretion; it is only for use in teaching situations. This condition is typically implicit, it is not expressed in personal social contracts but comes with the definitions and practices of the educational environments and professions (that is, social contracts at national level). Hence, it differs across countries. Physical educational environments make it easy to meet the contract terms, as each teacher is in control of the data. LA changes this as much data that may be sensitive is handled digitally, and the ways that this is done is not only beyond the control of teachers and students, but also often opaque and difficult for them to learn about.

This means that the policies of educational institutions become important. This chapter discusses higher education, but the issues discussed are arguably even more important to K-12 education as it concerns more students, younger students (and therefore also involves their parents) and generally a more diverse population.

1.6 Conclusion

The chapters in this book together bring up many issues pertinent to making learning analytics more *practicable.* They all focus on specific issues or practices and use different theoretical perspectives but for the purpose of discussing the overall perspective of 'practicability', we have provided an overview of the problem of making learning analytics practicable by using the concept of the *Information System Artefact* (ISA). The ISA consists of three integrated and mutually dependent sub-artefacts, *social, technical*, and *informational*. In the brief analysis of the chapters in the previous section, we provide glimpses of how the three sub–artefacts relate to each other in the different educational situations or aspects of learning that each chapter discusses. Throughout the chapters, it is clear that the *social artefact* is the most fundamental for practicability. Any substantive changes in information handling – content, process, format, technology used – will affect the social educational situations, and to be effective – or at all used – they will have to be understood and accepted by the practitioners involved. This is not to say that the *social artefact* – the way in which education is conducted – cannot or should not change. Quite to the contrary, practitioners – students as well as teachers – experience many problems or deficiencies in the way education is conducted and are likely to welcome changes, just like they have already done as concerns use of various other technologies. But the welcoming is contingent on them anticipating, and ultimately experiencing, benefits to their teaching and students learning. Therefore, an important key to successful large-scale implementation of learning analytics is the way teachers and students are approached. What is not practicable is not likely to be used.

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Chapter 2
Embedding Learning Analytics in a University: Boardroom, Staff Room, Server Room, Classroom

Simon Buckingham Shum

2.1 Introduction

In this chapter, I describe and reflect on the last 8 years at an Australian public university, inventing, piloting and evaluating Learning Analytics (LA) tools, leading in some cases to enterprise-wide deployment accompanied by extensive staff training and support. I will summarise this as conversations in the *Boardroom*, the *Staff Room*, the *Server Room* and the *Classroom*, reflecting the different levels of influence, partnership and adaptation that are required to introduce and sustain novel technologies in the complex system that constitutes a university, or indeed, any educational institution.

- *The Boardroom* symbolises engagement with the university's senior leadership, who need to understand how LA aligns with and advances their strategic priorities—since they expect returns on their investment in LA.
- *The Staff Room* symbolises engagement with the academics and tutors who need to understand in advance how LA could advance their teaching—since they expect returns on their investment of time and trust in introducing LA tools to their teaching practice.
- *The Server Room* symbolises engagement with the information technology service, who need to understand how LA fits into the university's digital ecosystem—since they need assurance that this meets architectural requirements, will not compromise security, and meet data governance requirements.
- *The Classroom* symbolises actual engagement with LA by students and teachers 'in the heat' of teaching sessions (face-to-face and/or online)—since if this does

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not go well, trust in the value of LA is undermined for either or both educators and students.

I suggest that without the ability to conduct these very different kinds of conversations, LA teams will struggle to sustain the adoption and scaling up of LA tools. The implication is that LA teams must have people who can engage competently with these stakeholders and the agendas and constraints under which they operate. These rooms are of course interconnected: without Boardroom backing, there are no resources to sustain LA; without the Staff Room conversations nobody will be aware of LA tools, which will never make it into their classrooms, and senior leadership will not hear positive feedback from faculties; without robust computing infrastructure, end-users' trust is eroded by unresponsive or unstable software; without IT approval, there is no case to argue to senior leadership for new development or procurement funds; and so forth. I hope, however, that the four rooms help rather than hinder, and serve as a *method of loci* mnemonic.

This chapter is intended to be very pragmatic, documenting aspects of our work that are typically not the focus in research papers, although the research-based invention and gathering of evidence is central to our modus operandi, and will be cited as relevant. So, this chapter is intended as a practice contribution, with links to online educator resources and practitioner stories illustrating what our work looks like in practice. I trust that this is of interest to readers seeking accounts of how LA tools can embed and scale in an educational institution.

2.2 "Learning Analytics": Scope and Definitions

Before proceeding, I should clarify the kinds of LA-enabled applications that provide the context for these reflections. Firstly, there are *LA dashboards*, namely, business intelligence style graphs/charts summarising student data of some sort. While such dashboards certainly keep the human in the decision-making loop, this does not increase human agency if they are overwhelmed by too much data, or uncertain how to interpret and act. Such *exploratory* visualisations place the burden on the user to explore efficiently, interpret appropriately and act responsibly.

We see various strategies in the field for addressing this risk:

- *When the target user is the student*, the cognitive effort to derive actionable insights from a novel visualisation risks undermining adoption unless suitably scaffolded through learning design that makes this a pedagogically valued and productive activity. As discussed later, a significant part of our work has been to make the effort required to reflect on LA feedback into a productive activity by integrating it into student activities and assignments as formally valued work. We have also implemented a principle of "embracing imperfection" with advanced LA tools, which seek to provoke mindful engagement by learners through critical engagement with AI (Kitto et al., 2018). Finally, our most recent work has begun to focus on increasing *feedback literacy* as a capability that both students and educators bring to the use of automated feedback.[1]

- *When the target user is an educator*, increased workload will also raise concerns about the return on investment (ROI)—we are requiring staff to trust that their efforts will be repaid. One strategy for addressing this is to keep the dashboards so simple that they are essentially like “walk up and use” information appliances (cf. public interactive tools like tourist guides and automated bank tellers). However, with more sophisticated displays requiring exploration, one must provide effective training that builds LA literacy (Corrin et al., 2016; Herodotou et al., 2020). Equipped with this literacy, educators gradually build their agency and skills to read the dashboard and act confidently, safely and ethically (Molenaar & Knop-van Campen, 2019; Li et al., 2021). This is analogous to pilots learning to fly by instruments when they lose direct visibility of the physical environment. To pursue the analogy, particularly with large cohorts, and especially in online learning, with limited visibility of one’s students, without dashboards and the competence to use them we might say that educators are somewhat “flying blind”. This approach—training teaching teams how to use complex dashboards—is exemplified by the in-house UTS Subject Dashboard[2] and commercial Canvas Analytics.[3]

An approach to mitigating the risk of gathering data whose interpretive effort outweighs the ROI, is that the LA (i) identifies significant patterns in the data rather than leaving this to the user, and (ii) lowers the effort required to take action. We take two main approaches to this. One approach is to focus on making LA dashboards *explanatory visualisations*, using ‘data storytelling’ as a design approach to actively communicate the most salient ‘take home’ messages, reducing the interpretive burden on the user. This approach is exemplified by tools such as the Nursing Simulation Teamwork Analytics (Fernandez-Nieto et al., 2021).[4]

The other approach has been to involve academics in co-designing educational technology tools that assign greater machine agency, that is, interactive web applications that provide *automated feedback* to either students or teaching teams. This approach negotiates the ROI trade-off in a different way, by changing the human-machine “allocation of function” (to use an old ergonomics term). This approach requires greater effort to configure the responses the tools should provide to differentiate feedback to different student profiles, but the tools then act autonomously, sending instant or scheduled feedback, 24/7, to potentially hundreds of students at a

[1] DAFFI 2020: Designing Automated Feedback for Impact symposium: https://cic.uts.edu.au/ensuring-automated-feedback-is-pedagogically-sound-daffi2020

[2] Subject Dashboard training: https://lx.uts.edu.au/events/overview-of-the-subject-dashboard-an-academic-perspective-28-february/ and https://lx.uts.edu.au/blog/2022/04/13/what-the-subject-dashboard-can-teach-you-about-your-students

[3] Canvas Analytics training: https://lx.uts.edu.au/collections/building-your-canvas-course/resources/canvas-new-analytics

[4] Nursing Simulation Teamwork Analytics: https://cic.uts.edu.au/new-video-captures-cic-health-collaboration-on-automated-feedback-to-nursing-teams

time, which is humanly impossible. This approach is exemplified by tools like AcaWriter[5] (Shibani et al., 2022; Knight et al., 2020) and OnTask[6] (Lim et al., 2020, 2021).

2.3 Boardroom

Securing Senior Leadership Support In 2010, the University of Technology Sydney (UTS) began to discuss what it might mean to become a "data intensive university", led by Shirley Alexander, the Deputy Vice-Chancellor for Education & Students (DVC-ES). This broad notion was inspired by the 'big data' transitions being witnessed in other sectors (health; retail; medicine; finance; leisure; etc.), and the emergence in education of the Learning Analytics community. Following several years' cross-university consultation involving the senior leadership, interviews with operational leaders, and audits of university data stores and flows (or lack thereof), what started as the "Data Intensive University" was renamed the "Connected Intelligence Strategy" as a broader, richer notion, and the Connected Intelligence Centre (CIC) was launched in 2014.

The importance of this preparatory work (Fig. 2.1) is not to be underestimated, since it led to senior leadership engagement and investment, and prepared the ground following launch, for the CIC team to work with stakeholders who were by then well aware of the senior backing behind it, and excited to engage.

As reflected in Fig. 2.1, CIC's mandate was very broad, namely, to catalyse greater data and analytics literacy among students, academics and professional

Fig. 2.1 Timeline showing initial UTS strategic consultation process 2011–2013 on what became the Connected Intelligence Strategy, to launch of the Centre in 2014 and subsequent activity

[5] AcaWriter orientation: https://uts.edu.au/acawriter and research https://cic.uts.edu.au/tools/awa Co-designing automated feedback on reflective writing with the teacher: https://www.heta.io/co-designing-automated-feedback-on-reflective-writing-with-the-teacher

[6] OnTask orientation: https://cic.uts.edu.au/tools/ontask

staff, and show the utility of LA, with three years to prove our value. CIC's organisational positioning outside the faculty structure emphasised the clear understanding that our mission was to add value to frontline business, providing data science insights to units spanning teaching, student support and research. The direct reporting to DVC-ES recognised LA as a distinctive, applied field requiring transdisciplinary, research-informed expertise that was not active in UTS. CIC was also given a faculty-like mandate to design and launch (i) a new Master of Data Science & Innovation degree, (ii) an introductory numeracy/data literacy course that faculties could permit their students to choose, and (iii) a PhD program dedicated to LA. The staffing of the centre was therefore critical, with great emphasis placed on interdisciplinary, research-active, academic ability in LA, strong communication skills, as well as human-centred design and software developers to prototype interactive tools.

Buckingham Shum and McKay (2018) diagnose the pervasive research/services divide in universities which can result in what in other organisations would be considered deeply dysfunctional: a data science research group can be using state-of-the-art computational infrastructure to solve societal challenges, a faculty-based research group can be tracking the most robust evidence about effective LA—all just 10 min walk over campus from the professional services data/analytics team who are struggling with outdated IT to address the university's strategic challenges, and no knowledge about how to design dashboards that educators will adopt. As we will see, this has implications for what happens in the Server Room, but where in the university organisational architecture the LA work has voice and visibility obviously plays out in the Boardroom. In reporting to the DVC-ES, I meet weekly with fellow directors who are leading UTS-wide student support, library services, and academic professional development in pedagogy and learning technology. This not only ensures that the DVC and directors are continuously abreast of our LA strategy and deployment, but in turn, our strategy can be aligned closely with these other facets of the student experience. CIC's data scientist also serviced these directors with reports, making the division the first in UTS to have its own data scientist to call on.

Aligning LA with Strategic Priorities It is important that LA's practical benefits can be positioned in terms of the university's strategic priorities, since this can also open access to resources to advance the work (often much more rapidly than competing for scarce public research grants), but accompanied of course by corresponding expectations of business outcomes. The UTS *Learning Futures* strategy provided the teaching and learning approach that was being embedded at institution-level, within which we needed to position our LA work. At the time of writing, our current *UTS 2027* strategy foregrounds a range of thematic priorities, against which our LA tools align.[7] For instance, our work on skills analytics is funded internally to advance the priorities on *Lifetime of Learning* and *Distinctive Identity* by informing prospective as well as current students about which courses will most likely equip them to achieve their career aspirations, engaging the public as well as enterprise learning

[7] UTS 2027 Strategy: https://strategy.uts.edu.au

partners.[8] The UTS *Learning.Futures2.0* strategy launched in 2021 had as one of its elements the use of *automated feedback*, in recognition of the progress CIC made.

Budget Boardroom conversations are naturally often around resourcing. While CIC secures some competitive external research grants (e.g., Office for Learning & Teaching; AUS Research Council; AUS Technology Network of Universities), we have been fortunate that compared to a faculty research lab, less of our time must be devoted to grant writing since we have core funding as an institutional innovation centre. That normally enables longer-term planning and staff retention, with the proviso that the centre is demonstrating its relevance to UTS strategic priorities. Conversely, like all university units, CIC's budget drops in financially challenging times (whereas an external grant is guaranteed for its duration). The closest model, therefore, is with any corporate or government R&D lab, whose mission is to keep the organisation on the forefront of practice, with foresight of what may come over the near horizon. CIC started as a Strategic Project for its first three years, converted to core business on successful review by university leadership. The 2017 report documented a range of quantitative and qualitative indicators of impact, including the level and types of engagement CIC had across UTS, the numbers of students and staff using our LA web applications, data science consulting across business units, the success of the Masters degree program, and the international standing of UTS in the LA community. CIC has also received short-term funding for strategic projects, including several small, 1-year learning and teaching innovation grants partnering with faculties,[9] plus R&D developing skills analytics services[10] which integrate with other platforms, and advance university strategy around lifelong learning and the future of work.

Advancing Data/Analytics Pedagogy and Literacy There is scope for LA teams to help advance the university's agenda to be on the leading edge of pedagogy, delivering a future-focused student experience. *Transdisciplinary* teaching and learning are one of the hallmarks of UTS at undergraduate level (Baumer et al., 2020; Kligyte et al., 2022), opening opportunities for CIC to demonstrate the difference this could make to the teaching of data science. CIC designed, launched and coordinated the first transdisciplinary postgraduate degree at UTS, the Master of Data Science & Innovation (MDSI)[11] for its first three years before handing it over in 2018 to a new faculty dedicated to Transdisciplinary Innovation. The high degree of engagement that students had with state government and industry, often winning data hackathons,

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[8] UTS Tailored Recruitment Analytics & Curriculum Knowledge (TRACK) web applications: https://cic.uts.edu.au/track-data-informed-insight-into-how-the-uts-curriculum-maps-to-careers

[9] Examples of internally funded CIC learning and teaching innovation projects partnering with faculties: https://cic.uts.edu.au/category/project/uts

[10] TRACK: data-informed insight into how the UTS curriculum maps to careers: https://cic.uts.edu.au/track-data-informed-insight-into-how-the-uts-curriculum-maps-to-careers

[11] UTS Master of Data Science & Innovation 2015–17: https://cic.uts.edu.au/professional-development/mdsi

showcased the distinctive quality of UTS students, providing examples for senior leaders to point to. While not all LA centres run Masters programs, far more can offer shorter training programs which demonstrate how they are advancing their university's strategy by upskilling students and staff in data and analytics. CIC also designed and ran *Arguments, Evidence & Intuition*[12] as an elective course for any student, advancing the institutional priority to improve numeracy and data literacy. As UTS developed its online learning program in 2018, material from this was adapted and extended to create free, open modules such as *What Does Facebook Know About You?* and others.[13] These courses were accompanied by accessible communications for general readership to provoke greater curiosity in the topics.[14] This capacity to create engaging learning experiences does of course require the right kinds of academic staff, bringing teaching skills likely to be missing if an LA centre is staffed only with data scientists and software developers—another strong argument for entwining LA teams with academic teams.

Keeping Faculties Informed and Onboard CIC presents briefings to Faculty Boards and Associate Deans with oversight of their faculty's teaching, where it has been important to demonstrate the relevance of CIC's work to each faculty. Depending on the collaborative partnerships forged with that faculty's academics, this might include examples of automated feedback tools in use within their degree programs, including evidence of the responses of the teaching team and students to such novel technology, and the impact on student experience and outcomes. This emphasises the need for the LA centre to have the capability to evaluate the impact of LA pilots, in order to create an evidence base (detailed in next section).

Statistical Consulting Complementing deployments of LA-enabled educational technologies, are more conventional statistical analyses of institutional data ("academic analytics" to use the terminology of Long & Siemens, 2011). CIC hired a data scientist in a non-academic role to provide statistical analyses in response to business questions faculties and student support units faced. While we referred to this as 'consulting' this was not for fee, but a reference to the mode of engagement with our 'clients', and with no expectation that this should lead to research publications, which is always a legitimate concern when PhD students and postdoctoral researchers are asked to undertake such work. To take one example, *Is there any*

[12] UTS Arguments, Evidence & Intuition elective 2015–17: https://cic.uts.edu.au/professional-development/aei

[13] UTS Open Taster Modules developed by CIC academics Kirsty Kitto and Simon Knight, to build introductory data and statistical literacy: What Does Facebook Know About You? https://open.uts.edu.au/uts-open/study-area/analytics%2D%2Ddata-science/critical%2D%2Dcreative-thinking/what-does-facebook-know-about-you Journey Through Data: https://open.uts.edu.au/uts-open/study-area/analytics%2D%2Ddata-science/critical%2D%2Dcreative-thinking/journey-through-data Statistical Thinking: https://open.uts.edu.au/uts-open/study-area/analytics%2D%2Ddata-science/data-science/statistical-thinking

[14] Simon Knight and Kirsty Kitto (2018), *4 Ways to Build Data Curiosity.* UTS Futures: https://lx.uts.edu.au/blog/2018/08/21/4-ways-build-data-curiosity

evidence that the student cohort who spent their second year abroad benefited from this, compared to their peers who stayed at home? This required a comparison with students on the same degree program and elective courses, but without the international year. To be robust, this analysis involved tens of thousands of individual student grades over many years. The results did indeed demonstrate a positive impact, enabling the faculty to be confident in making evidence-based claims when advertising their international program. CIC has also serviced non-faculty units with statistical analyses, such as a student support centre who asked, *Can we claim that students who come to us for academic support benefit in terms of their grades?* The analysis demonstrated how the gap had closed over successive years for students who had sought support.

Data Storytelling It is common that presentations for senior leaders produced by data scientists are not always the most intuitive for their audience, typically packed with detail that can overwhelm. The field of "data storytelling" offers a set of information design principles that we have adopted to provide helpful guidance for multimodal LA feedback (Echeverria et al., 2018), but also use to refine the presentation of our more conventional statistical analyses to be more engaging for non-specialist audiences,[15] and to advise other groups developing dashboards.[16] No matter how rigorous our analysis, if we lose our audience, we don't do ourselves justice, and the work may have no impact.

2.4 Staff Room

Walking in the Shoes of Academics If we can't talk to teachers and gain their confidence, we're not going to get very far deploying LA apps in their classrooms. Consequently, CIC's appointments included academics who were also experienced educators. We know what it takes to teach students at undergraduate and postgraduate levels, using blended learning pedagogies. We appreciate the constraints on what is possible in a given classroom setting, and the challenges of coordinating other academics and casual tutors around a course innovation. We know the pros and cons of the different learning technologies available. We know what it is like to grade, and to receive critical feedback in student surveys. We know the pressures on academics to publish research, as well as teach. Without members of the LA team who appreciate the lived experience of academics and tutors, there is a risk that unrealistic assumptions are made in the design and deployment of LA, as evidenced, for instance, in the literature now emerging around obstacles to educators' adoption of LA dashboards (Kaliisa et al., 2022).

[15] A Brief Introduction to Telling Stories with Data: https://lx.uts.edu.au/events/brief-introduction-telling-stories-data

[16] UTS Subject Dashboard: educator stories: https://lx.uts.edu.au/blog/2022/04/13/what-the-subject-dashboard-can-teach-you-about-your-students

CIC's team has a sound understanding of what it will take for academics to pilot an LA tool with their students. The team can also share with them the evidence we already have from previous uses in UTS, support them in deployment to minimise the risks of technology failure, and help them co-author peer reviewed publications that add to their research profiles. An important element in our approach to LA is alignment with learning design (LD). In brief, while LD specifies what you hope will happen, LA tells you (partially) what's actually happening (Lockyer et al., 2013). LD provides the context that enables the meaningful interpretation of analytics: whether or not a pattern of usage is productive or not depends on what the students were being asked to do. We detail elsewhere the framework that has been refined over the years to enable the contextualisation of LA to different courses (Shibani et al., 2019), and have documented the student and teacher experience with different tools. Rigorous research around the adoption of LA also provides the evidence base when making a case to senior leaders—an evidence base that is in fact more robust than is typically available for any other learning technology product the university deploys.

Reframing LA as Automated Feedback For most academics other than the computing disciplines, "analytics" is either a meaningless term, or deeply suspect, part of the Big Data rhetoric about which many are justifiably sceptical. For those that care about student outcomes and creating a high quality student experience, however, the concept of feedback is familiar, albeit challenging. The massification of higher education has left academics and tutors with scarce time to devote to giving each student the personal care and feedback they would like to offer. For this reason, we talk much more these days about *automated feedback* than LA—emphasising that we are not automating people out of jobs, but equipping them to co-design how they want to use such tools to expand their capabilities as a teaching team, as part of a richer feedback ecosystem.[17] This coincides with a UTS-wide priority to increase *sense of belonging*, and improve *feedback literacy* among both students and educators.

Those are the kinds of conversations to hold in the Staff Room. It can also be seen that from an LA strategic perspective, there is no point in gathering data if it is not actioned. The imperative to show the value of data-intensive tools motivated the focus on automating the analysis and actioning of data, with personalised feedback which now spans dispositional feedback, skills feedback, collocated teamwork feedback, writing feedback and LMS engagement feedback. Each of these is the focus of evaluation studies that clarify the student and staff response, and contribute to the peer reviewed research evidence base.

[17] Automated Feedback: UTS educator briefings https://lx.uts.edu.au/blog/2021/06/11/automated-feedback-looking-back-forward

2.5 Server Room

LA Tools Must Be Robust and Usable All of the preceding considerations establish the organisational and human context in which LA can take root and thrive, and are, arguably, the most difficult conversations to have, given the inertia of changing organisational processes, and upskilling staff. However, if the technology itself is not usable, stable, secure, scalable, on-brand, and supported when problems arise, all this will have been for nought. As discussed in some detail by Buckingham Shum and McKay (2018), there are inherent tensions in universities between developing innovative, research-inspired LA in-house because there are no products that provide such advanced capability, and evolving these into 24/7 enterprise grade services. The incentives and skillsets required to do each of these are rarely found in the same team. CIC's rationale, organisational position and modus operandi require a particular organisational structure, which aims to blend research-inspired innovation with reliable service delivery.

In contrast to building a research concept demonstrator, LA research involving student-facing tools must scale elegantly, which is aided immeasurably by contemporary cloud computing infrastructure that can expand and contract capacity dynamically depending on the load. Tools must also be usable, and as they move into mainstream use, university branded. CIC's work emphasises human-centred design as a mindset, but it is still easy to underestimate the effort it takes to refine a user interface to the point where it is 'walk up and use', or close to this following minimal orientation. This typically requires liaison with the UTS IT Unit's graphic and interface designers, and accessibility testing services.

One way to sum up the LA software transition required is the move *from LA project to LA product.* LA projects are the bread and butter of research groups, typically lasting for a few years, in order to investigate and demonstrate exciting new research ideas, after which the team moves onto the next grant or the next PhD student. Even if there is continuity in the software development, there are critical steps to this becoming a recognised part of the learning technologies ecosystem, governed by the IT services division, and which many/most research projects do not reach.

These include:

- institutionally approved user authentication ("single sign-on") to provide a seamless and trusted user experience for students and staff;
- auditing of the software to ensure compliance with preferred/required language and architectural design
- security of code and APIs
- cloud hosting in infrastructures approved for security and location (student data should not ideally leave our State, or at least stay in Australia, which may require additional vendor effort);
- cloud scaling strategy to meet variable user demand;
- integration of the tool into support services, so that should a student report a problem, there is a workflow to handle the issue.

Satisfying the above technical requirements in order to deploy at scale requires many conversations, learning new business processes, documentation, and the building of trusted partnerships. The LA team must be able to “talk tech” in the server room, and build confidence in the IT services division that they know what they’re doing, and will not be responsible for a data or security breach that could compromise the university, or poor branding/user experience.

2.6 Classroom

The classroom is, of course, where we hope to see LA-enabled learning technologies—once we successfully negotiate the Staff Room and Server Room. The software must be both sufficiently usable and robust when deployed in the pressure of live lectures and workshops, where a traumatic experience with broken technology can dissuade academics from risking it a second time. We therefore work closely with academics to maximise the chances of a positive experience for them and their students.

Human and Technical Support in the Classroom If a whole cohort of students will be using a tool in a classroom, we need to ensure that the system can handle possibly hundreds of simultaneous logins, which for a computationally intensive tool like our writing feedback app, might require a responsive increase in cloud resources. CIC may field researchers to present live, or pre-recorded video briefings, in introducing a new tool, to relieve extra load on the academics. The classroom extends, naturally, to the online world. We build orientation portals and share news stories for students and staff,[18] and construct modules in Canvas that provide an extended introduction, with activities to scaffold use of a new tool.

Sound Learning Design Safety Net A ‘safety net’ that can be provided in case LA tools do fail for some reason, which is to ensure that the activity in which students were intended to use the tool is still a meaningful, productive activity without the tool. We have detailed how this learning design strategy has been used with our writing feedback tool in courses, by modifying well-designed assignment activities with the optional use of AcaWriter (Shibani et al., 2019, 2022).

Explaining LA Relevance to Students It is critical that students understand the relevance of an LA-enabled tool to their studies and career aspirations. The faculty academics are the best people to explain this to their students, and often bring a

[18] UTS orientation for LA tools: Learning Journeys dispositional feedback https://LearningJourneys.uts.edu.au and AcaWriter writing feedback https://uts.edu.au/acawriter

passion and energy that excites students, which may be missing if CIC designs and delivers the presentation (students don't know us, and we lack the domain knowledge), or if the introduction is left to the many casual tutors who are employed to support teaching (but who are less motivated about the new tool). Since academics cannot attend every class in person, we now have a number of videos from academics introducing the tool to their students, explaining why as a lawyer, accountant or pharmacist (to take three examples) they need to care about making rhetorical moves visible in their writing.[19]

Evaluating What Actually Happens Central to our approach is to evaluate, using quantitative and qualitative methods, what *actually* unfolds in the (physical/online/blended) classroom, and the stakeholders' *experiences* of these, as well as *process and product* impacts. As detailed in our research articles, these deployments in authentic teaching contexts are extremely illuminating regarding how students and educators engage (or not) with the LA tools, clarifying both the enabling factors as well as the obstacles (e.g., technical; usability; pedagogical; logistical) and strategies for resolving them. Explicit attention is paid to questions such as whether academics feel that the time investment required to introduce a new tool was justified (Shibani et al., 2020); students' emotional responses to receiving novel forms of automated feedback using AI (Lim et al., 2020); and privacy values about who should be able to see and act on LA visualizations of student activity (Martinez-Maldonado et al., 2020). Research studies can provide a detailed understanding of whether students are able to make effective use of automated feedback, leading to pedagogical interventions to more effectively scaffold their use of the tool. For instance, Shibani et al. (2022) describe the creation of annotation tasks for students to encourage deeper, critical engagement with the automated writing feedback, while studies of the use of the OnTask tool by Lim et al. (2021) documented negative student responses to automated 'nudges', who suggested that metacognitive prompts in the form of questions could be more productive. Regarding dispositional analytics, Barrat-See et al. (2017) report qualitative and quantitative findings from piloting the CLARA tool with nearly 3000 students, distilling a more detailed internal report that provided the basis for procurement of the product. Research studying student responses to OnTask has similarly provided the evidence base needed to justify ongoing investment (Lim et al., 2020, 2021, 2022).

Design iterations tend to follow the semester cycle, as lessons are learned from each deployment, but may take longer depending on other factors. Consequently, while academics and instructors will see improvements (and some academics co-author research papers with CIC), most students will not, unless a subsequent course also uses the same tool. At this stage, usage of these tools is not so ubiquitous at UTS that degree-wide adoption is the norm, but we are now beginning to have such conversations, which represents another significant milestone. However, as certain

[19] AcaWriter educator resources with UTS examples: https://www.uts.edu.au/research-and-teaching/teaching-and-research-integration/acawriter/educators/how-acawriter-being-used-uts

tools reach a level of maturity that they can be released to all students for self-initiated usage (AcaWriter; Learning Journeys; TRACK), this increases the chances of students seeing improvements over the longer term, as they would expect to see in the commercial products they use.

Academic Professional Development and Support The importance of ongoing staff development with LA tools cannot be overstated. There is a longstanding, large graveyard of ed-tech innovations that fail to move "beyond prototypes" (Scanlon et al., 2013), with a key challenge being lack of investment in staff to help them use new tools effectively and with confidence. We therefore run regular briefings in the central campus "Learner Experience Lab" (https://lx.uts.edu.au) where academic development workshops are run for staff, introducing the different tools, explaining what they do (and don't do), showing examples of their use in UTS, and inviting follow-up conversations for academics to explore in detail how they might introduce the tool into their course.[20] We have started to convene small communities of practice (Lave & Wenger, 1991), which enable academics with different levels of experience to meet and share how they are using a tool. This is also a forum where we as researchers can share the latest technical advances, teaching practices and research evidence, or convene workshops to prioritise new features for future releases or products. The academics may become co-authors with us when writing up collaborations, and may also present/publish the work in their own disciplinary communities concerned with education (engineering education, pharmacy education, etc.).

Doctoral Researchers It is labour-intensive work to partner with an academic and walk with them as they introduce LA-enabled tools for the first time, not only for themselves, but often, for the degree program they teach, and in their faculty. Particular acknowledgement is deserved for the contribution that doctoral researchers can make in this regard, since CIC doctoral researchers need to bring not only a passion for their research, but a commitment to supporting the academic(s) with whom they work, and strong interpersonal skills capable of sustaining long term collaborations. Students may not be in the Boardroom, but are part of the Staff Room conversation that conceives the partnership, and very hands-on before/during Classroom engagement when the stakes are at their highest for the educator in front of students, and for the students using new ed-tech.

Good PhD students add critical capability to the team, with the time and skills to explore new possibilities with academics, in order to co-design LA tools that they come to trust sufficiently that they are ready to deploy them with their students. Of

[20] For instance, see LX Lab briefings on Automated Feedback
https://lx.uts.edu.au/?s=%22automated+feedback%22
- AcaWriter https://lx.uts.edu.au/?s=acawriter
- OnTask https://lx.uts.edu.au/?s=ontask
- TRACK https://lx.uts.edu.au/?s=track
- Learning Journeys https://lx.uts.edu.au/?s=%22learning+journeys%22

course, a PhD is a high risk undertaking at the best of times, and working in authentic contexts with academics and paying students raises the stakes, but it is also exhilarating when it goes well. Our students have used combinations of Design-Based Research and Human-Centred Design as methodologies to structure such research, give academics a voice, minimise the risks, and learn from each iteration. Naturally, the academic supervisors play a critical role in managing the risks for all stakeholders, as students seek to test advanced concepts within the constraints of all four Rooms discussed here.

Beyond Early Adopters Within months of launching, CIC ran a series of briefings open to all academics and tutors. I introduced the topic of LA, explaining our strategic interest in building transferable, lifelong learning competencies, and demonstrating the kinds of approaches that were now becoming available for academic writing, learning dispositions, and embodied learning. We were seeking early adopter partners and invited academics to 'pitch' to CIC (using a simple template) the match they saw between these kinds of LA, and teaching challenges they were experiencing. This launched our first six or so faculty collaborations. Several years later, there was a distinct sense of passing an important milestone when these academics presented their use of LA to their colleagues within their faculties, and at the annual UTS Learning & Teaching Forum, as well as on national and international stages. These academics are typical early adopters, who are interested in new technology, and open to making changes in their teaching in order to take advantage of the new affordances. Their courage, however, is what encourages enquiries from their colleagues (in UTS, and nationally/internationally) about using LA in their teaching. Compared to hearing LA researchers enthuse about their work, seeing a trusted academic colleague describe their positive experiences using LA to teach often speaks volumes more to academics.

We now have such 'second generation' academics using all of our LA tools, as well as academics 'inheriting' courses that pioneered LA, who now requiring briefings because 'this is a tool used in this course' just like other ed-tech products. We are also beginning to discover by accident that an academic has introduced one of our tools without engaging at all with CIC, which is both exciting (this has grown so big we can't keep track of it), but also concerning since it exposes weaknesses in the induction processes that we have sought to establish (especially if they are introducing the tool as something of a 'bolt on' rather than as an integrated part of their course's learning design). We are considering whether teaching teams should need a 'driving licence' before they jump behind the wheel of our tools, as a quality control measure, or whether culturally, this will not be accepted.

2.7 Closing Reflections

I have discussed and reflected on each room as we have walked through them. In this final section, I will touch on a couple of topics that span all of them.

Questions around data ethics, algorithmic bias, explainable AI, and so forth are rightly to the fore of many people's minds when we discuss LA. This is a topic that CIC has engaged with academically (Kitto & Knight, 2019; Khosravi et al., 2022), providing the university with a deep understanding of the issues. It brings an unusually high degree of control over the LA we design and deploy, compared to procuring commercial products with limited algorithmic transparency, or permitting only minor re-configuration/modification. This permits us to adopt more human-centred design processes that engage stakeholders in evaluating early prototypes, building the trust required to deploy live.

While all LA research is governed by the Human Research Ethics Committee, access to data must also be approved by the DVC(ES) who must be briefed about the project, and integrations of data from more than one UTS unit must be declared in Data Sharing Agreements. Students must be able to give informed consent, and we must be able to exclude their data if they choose to withdraw. Visualisations can have an aura of truth around them for educators and students, but if it leads to misinterpretation and inappropriate action, poor information design suddenly takes on ethical implications.

Most recently, we have investigated a 'deliberative democracy' model for in-depth consultation with UTS staff and students about the principles that should govern the use of LA (and now AI) in learning technologies, with promising results (Buckingham Shum, 2022). This modelled a structured, participatory and rewarding process for tech ethics consultation, with a concrete deliverable, and helped to catalyse the drafting of a UTS AI ethics policy. At the time of writing, members of this staff/student team are reviewing the principles they proposed against the draft AI Ethics policy, maintaining their voice in shaping responsible technology governance. CIC has also convened a movie screening and panel debate to engage the UTS community with the ethical implications of Big Data in society.[21] Initiatives such as these are designed both to educate the university community, and build trust that UTS is deploying LA in a responsible manner, since no matter how usable and technically sound the LA may be, if the community loses trust this could be hard to regain.

To conclude, it is a privilege to be given the opportunity to shape an institutional innovation centre charged with advancing data literacy, and LA-enabled learning and teaching, with the freedom to hand-pick a team whose expertise covers applied, transdisciplinary research, human-centred design, full-stack software development and enterprise integration. I hope that the reader leaves with a clearer sense of how our journey has unfolded, since the "back room" conversations are rarely foregrounded in LA literature. In order to deploy LA-enabled tools in authentic contexts, we must sustain, and manage the interdependencies between, conversations in the Boardroom, Staff Room, Server Room and Classroom. And as in any meaningful conversation, it comes down to trust.

[21] The Human Face of Big Data: public screening and panel debate https://cic.uts.edu.au/events/human-face-of-big-data-movie-panel

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Chapter 3
Applying and Translating Learning Design and Analytics Approaches Across Borders

Bart Rienties, Igor Balaban, Blazenka Divjak, Darko Grabar, Barbi Svetec, and Petra Vondra

3.1 Introduction

The COVID-19 pandemic has accelerated the use of digital technologies in education (Buttler et al., 2021; Holzer et al., 2021; Divjak et al., 2022b), including design, instruction, assessment and learning analytics (LA), but there is still a noticeable gap between potential and actual use of technology and LA in particular (OECD, 2021; Viberg et al., 2018). This gap has been central to the emergence of a parallel research area: learning design (LD) (Conole, 2012; Macfadyen et al., 2020). In order to support the LD process, a range of LD approaches have been developed over the years (Macfadyen et al., 2020; Wasson & Kirschner, 2020; Conole, 2012; Laurillard et al., 2013). One prominent approach that originated from work dating back to 2004 is the Open University Learning Design Initiative (OULDI).

This OULDI approach has been gradually conceptualised (McAndrew et al., 2005; Conole, 2012; Cross & Conole, 2009), tested (Van Ameijde, 2015), implemented (Toetenel & Rienties, 2016; Rienties et al., 2017, 2018), and re-designed (Ferguson et al., 2015; Hidalgo & Evans, 2020; Holmes et al., 2019; Nguyen et al., 2018a) over the years at the Open University UK (OU). LD and OULDI in particular is a structured design, specification, and review process. OULDI is focused on ‘what students do’ as part of their learning, rather than on ‘what teachers do’ or on what will be taught (Toetenel & Rienties, 2016). In a range of studies it has been

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shown that using these OULDI approaches are strongly predictive how students learn on a week-by-week basis (Nguyen et al., 2017, 2018a; b; Rienties & Toetenel, 2016; Rizvi et al., 2022), help educators to make real-time learning analytics decisions (Hidalgo & Evans, 2020; Holmes et al., 2019; Olney et al., 2020; Rienties et al., 2017, 2018; Boroowa & Herodotou, 2022), and improve the predictive modelling of student behaviour using the flagship OU Analyse predictive LA tool (Herodotou et al., 2020; Boroowa & Herodotou, 2022). Beyond the direct impact of OULDI on how the OU and its 7000+ academics and educators use LA on a daily basis, the use of the OULDI approach has resulted in an impact on the understanding, learning, and practice of 2000+ university educators over a dozen countries, including Belarus (Olney et al., 2020), China (Olney et al., 2021), Kenia (Mittelmeier et al., 2018), South Africa (Greyling et al., 2020), and the UK by shaping their understanding and implementation of LD.

In this book chapter we will critically reflect on how approaches like OULDI can be adopted, adjusted and refined to fit local and specific needs. It is well documented in adoption literature in general (Katz & Allen, 1982; Hauck et al., 2020) and LA literature in particular (Dawson et al., 2018; Tsai et al., 2020; Viberg et al., 2018) that one successful approach that works well in one institution or context cannot be "automatically" transferred to another without taking into consideration the specific cultural, organisational, and national characteristics. We will explore what we have learned from refining the OULDI approach to a new approach called Balanced Design Planning (BDP) which originated inter alia from three European projects run by University of Zagreb, Faculty of Organization and Informatics (FOI), namely eDesk, Teach4EDU, and RAPIDE (Divjak et al., 2022a). Three versions of the BDP approach (i.e., concept, dashboard, tool) have been developed and tested with 64 practitioners from ten institutions in nine countries in 2021/2022. At the moment of writing this book chapter the first real-life applications of these BDP designs developed by educators are being tested with students. As actual learning behaviour and cognition data of students engaging with these BDP approaches are not yet available we will therefore primarily focus on our lessons learned of how the BDP approach was developed and tested with these practitioners. We hope that by sharing our lived experiences others will benefit from our lessons learned, and how you could improve adoption of externally developed approaches in your own context.

3.2 Learning Design, OULDI and Learning Analytics

There is a growing interest in coordinating LD with LA, as the two can mutually provide valuable input. According to Lockyer et al. (2013), LDs can serve as a approach for the design of LA supporting educators' teaching and learning decisions, and LA can provide more holistic information on the impact of learning activities. In the early conceptualisation stage of LD with LA Lockyer and Dawson (2011) stated that the integration of LA and LD may support the understanding of student behaviour and provide recommendations needed when learning behaviour is not aligned with the pedagogical intention. However, it has been stressed by several authors (e.g., Hernández-Leo et al., 2019; Macfadyen et al., 2020) and two recent reviews (Mangaroska & Giannakos, 2019; Wasson & Kirschner, 2020) that, when it comes to linking the two areas of LD and LA, initiatives are sparse and often small in scale, and there is no holistic approach and guidelines that would support its full exploitation.

One notable exception is the LD and LA work conducted at the OU (e.g., Conole, 2012; Rienties & Toetenel, 2016; Toetenel & Rienties, 2016; Wasson & Kirschner, 2020; McAndrew et al., 2005), which has implemented both LA and LD approaches across its hundreds of online distance learning courses (Boroowa & Herodotou, 2022; Herodotou et al., 2020; Hidalgo & Evans, 2020; Holmes et al., 2019). In terms of LD, learning activities are categorised in OULDI according to seven main types of what learners do (i.e., assimilative, finding & handing information, communicative, productive, interactive, experiential, assessment), as indicated in Table 3.1. OULDI is supported by a simple set of tools and resources that enable a student-activity based approach that puts the student experience at the heart of curriculum design. These seven activities were distilled from intensive co-development by six UK universities in terms of mapping what common activities educators often design when delivering a teaching and learning experience within a course/module (Conole et al., 2008). By embedding LD with state-of-the-art LA approaches since 2014 the OU has also been trailblazing research on the OULDI approach (Rienties, 2021).

For example, Toetenel and Rienties (2016) analysed 157 LDs developed in the OU using OULDI. Results revealed that the majority of educators used two types of learning activities most widely, namely assimilative activities (M = 39%, SD = 17%:

Table 3.1 The seven Open University learning design initiative activities

LD activity	Details	Example
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate
Interactive/adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate
Assessment	All forms of assessment (summative, formative and self-assessment)	Write, Present, Report, Demonstrate, Critique

Toetenel and Rienties (2016), adapted by Balaban et al. (2021)

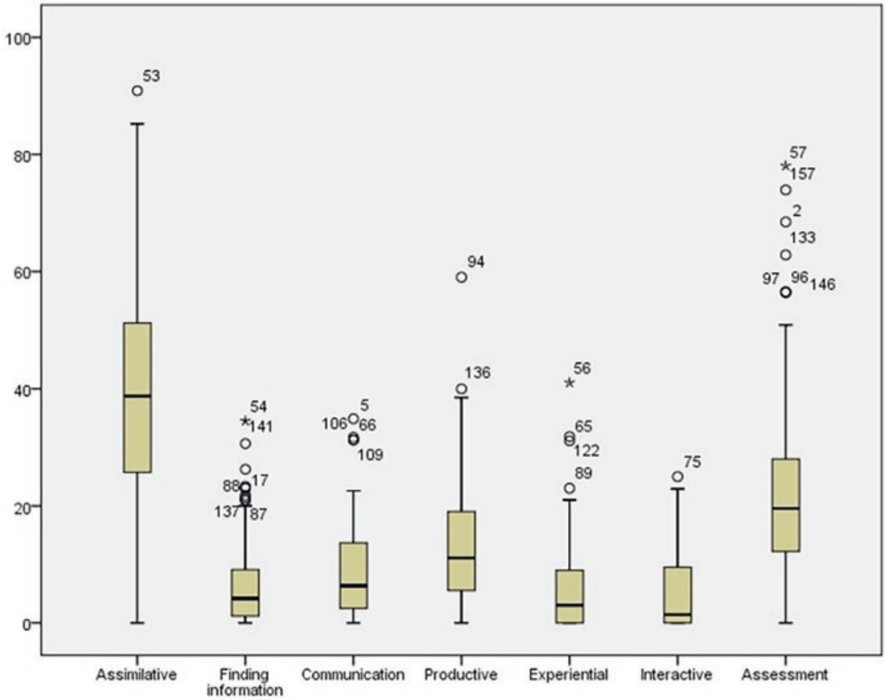


Fig. 3.1 Boxplot of 157 learning designs at OU (in percentages). (Source: Toetenel and Rienties (2016)

reading, watching videos and listening to audio) and assessment activities (M = 22%, SD = 15%). As indicated in Fig. 3.1 the categories of productive (M = 13%, SD = 10%), communicative (M = 8%, SD = 7%), finding information (M = 7%, SD = 7%), experiential (M = 6%, SD = 8%) and interactive (M = 5%, SD = 7%) were relatively little used on average. However, as is visible by the relatively large standard deviations, substantially different practices were found. Some educators did integrate substantially more productive and communicative learning activities, while others mainly focussed on assimilative and assessment activities.

Obviously, it is one thing being able to map how educators design and implement online learning activities, but another is whether (or not) LD influences learners' behaviour and academic outcomes, and whether these could be used for LA applications. In one of the first large-scale empirical studies finding a strong link between LD and academic outcome, Rienties and Toetenel (2016) used multiple regression models to link 151 modules taught in 2012–2015 at the OU and studied by 111,256 students with students' behaviour. Findings indicated that the primary predictor of academic retention was the relative amount of communication activities (e.g., student to student interaction, student to educator interaction). The findings indicated that a 1% increase in learning activities related to communication would increase pass-rates of modules with 0.5%. Furthermore, the way educators designed the online activities had a significant impact on student engagement and student satisfaction (Rienties & Toetenel, 2016).

Follow-up temporal analyses by Nguyen et al. (2017) on a week-by-week basis of how educators learning activities designed for say week 3 influenced students' behaviour in say weeks 1–6 with 72,377 students showed that 69% of how students engage on a weekly basis is a direct result of how educators design courses. In other words, two-thirds of study engagement and success of students is directly related to how educators design online learning activities. This is a tremendously important finding, as how educators create, design, and implement learning activities has a substantial impact on learners' success.

In a recent study looking at LDs in Massive Open Online Courses (MOOCs), Rizvi et al. (2022) used process mining techniques to inspect trace data for 49K learners enrolled in ten large FutureLearn MOOCs. They examined whether (or not) differences regarding the number of assimilative activities (articles and videos), communication activities (discussions), and assessment activities (quizzes) within a MOOC could be used to predict learners' persistence, and why learners engaged differently. The quantitative and qualitative findings indicated that LD decisions made by Western educators were mainly beneficial for Western learners, while learners from other geo-cultural regions either had to adopt a new learning approach, or were more likely to drop out. As argued by Rizvi et al. (2022) "[u]ntil we reach the (difficult yet attainable) milestone of a flexible, culturally adaptive MOOC LD, we recommend taking a balanced approach by combining different types of learning activities, not just video-based, or reading MOOCs." In other words, there is substantial evidence from research across the OU that the way teachers design their online courses using LD has a substantial influence on how students are engaging with these learning activities.

As indeed argued by Wasson and Kirschner (2020) who reviewed the adaptation of LD in Europe, the OU is one of the few institutions that have adopted LD and LA at scale. Perhaps more importantly, the OU has provided a range of empirical studies that have linked decisions made by educators in terms of LD with what students are actually doing, and how this informs the OU LA practices (e.g., Holmes et al., 2019; Nguyen et al., 2017, 2018a, b; Rienties et al., 2017; Rienties & Toetenel, 2016; Rizvi et al., 2022). For the development, review or redesign of modules, the OU uses a process of so-called "module mapping". Beginning with a stakeholders' workshop, in which the various possible LD activities are discussed in the context of the module being designed, the module's initially intended LD is analysed and subsequently presented back to the module team as a combination of graphics and text (by means of the OU's Activity Planner visualisation tool), as illustrated in Fig. 3.2. The aim is to make explicit the module teams' otherwise tacit LD decisions so that they might consider whether amendments to their LD might enhance the quality of their module (Balaban et al., 2021; Toetenel & Rienties, 2016).

As illustrated Fig. 3.2 in total 41% of learning activities for this introduction to engineering course were labelled as assimilative in total, whereby for example in week 17 six hours were pencilled in by the educators for students to work on assimilative activities, one hour on finding information, one hour on productive, two hours

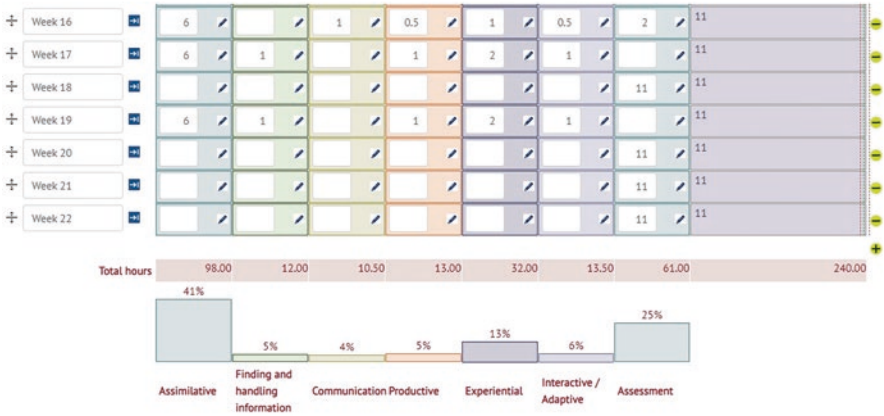


Fig. 3.2 Learning design of introduction to engineering. (Source: Rienties (2021))

on experiential, and one hour on interactive activities. In week 19 a range of productive and experiential activities were included, while the last three weeks were designed for preparation for the final assessment. By mapping and visualising the learning activities educators can ensure that appropriate workload balancing is introduced, and communicated to students.

While the above studies indicate that the OULDI approach works well to distil how educators design distance learning courses at the OU and how students react to these mostly online courses, whether (or not) this approach also works for non-distance learning institutions needs more exploration. The OULDI approach has been made available online using a Creative Commons license (Van Ameijde, 2015). Nonetheless, while there is some evidence of institutions adopting some of the OULDI design principles (e.g. Greyling et al., 2020; Mittelmeier et al., 2018; Olney et al., 2020, 2021), few institutions have actually adopted the OULDI approach at scale, or redesigned the approach to fit their own needs.

Indeed in a review on 10 years of LD for a special issue on LD and LA in *Journal of Learning Analytics*, Macfadyen et al. (2020, p. 10) indicated that "we need further research on educator design practices, particularly as they engage with learning analytics and other kinds of teaching and learning evidence. Understanding how educators make design decisions will help us develop better ways to support them in their design work, create an integrated environment of learning and teaching design, delivery and analytic systems, and foster institutional design climates". In particular as most LA and LD approaches have primarily been developed, tested, and implemented within the boundaries of a respective institution, there is a need to explore whether these such approaches can be generalised, adopted, and scaled at other institutions.

As argued by Dawson et al. (2018, p. 237), "the pace of adoption of analytics within education organizations can be categorized as at best sporadic, and at worst resistant". This was again confirmed by a review of LA adaptation in Europe, whereby Tsai et al. (2020, p. 2) argued that "empirical studies on the deployment of

LA in HE are notably small in scale, although there have been a paucity of nation-wide investigations". Indeed, very few institutions adopt and readjust "successful" approaches developed in other institutions. In part this is a result of the Not Invented Here syndrome (Katz & Allen, 1982), whereby people and organisations tend to prefer to adjust, adopt, champion or tinker their own approaches rather than using approaches that have been proven successful in other organisations. In part this is a result of strategic decision making processes amongst leaders of institutions (Dawson et al., 2018; Tsai et al., 2020), and in part it is a natural tendency of people to be resistant to change (Herodotou et al., 2020).

In the remainder of this chapter we will describe what we have learned from implementing, redesigning, fine-tuning and adapting the OULDI approach to meet the needs of three European Erasmus projects, namely Digital and Entrepreneurial Skills for European Teachers eDesk (https://edeskeurope.eu/), Accelerating the transition towards Edu 4.0 in HEIs Teach4EDU (https://teach4edu4-project.eu), and Relevant assessment and pedagogies for inclusive digital education RAPIDE (https://rapide-project.eu).

3.3 Developing the Balanced Design Planning Approach

As described by Balaban et al. (2021) and Divjak et al. (2022a), when implementing an existing approach like OULDI into a different institutional context, it is important to critically evaluate the underlying design principles and ensure that these are fit for purpose. Using the principles of design science, Divjak et al. (2022a) implemented three tasks of the design cycle, namely problem investigation, treatment design, and treatment validation in order to develop the first version of the Balanced Design Planning (BDP) concept and tool, as illustrated in Fig. 3.3. The up-to-date version of the BDP Learning Design tool is free to use and available at https://learning-design.eu/.

The motivation for the development of the BDP concept and tool has been two-fold. First, at University of Zagreb a need was identified by educators to develop an

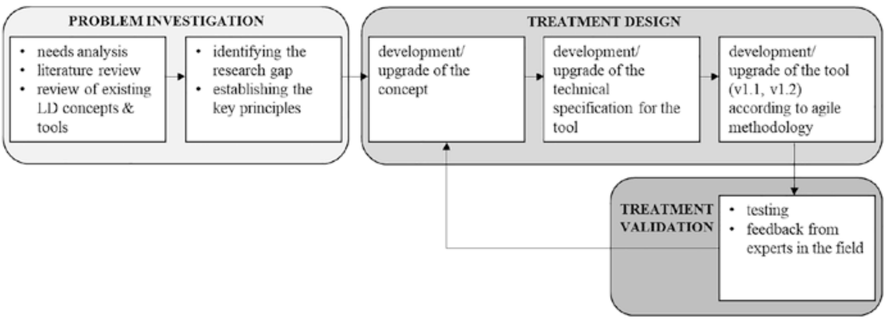


Fig. 3.3 Flow diagram of the BDP concept and tool design process. (Source: Divjak et al. (2022a))

LD approach which would put a strong emphasis on Learning Outcomes (LOs), not only at the level of a course, but also at the level of a study program, and their mutual vertical alignment (Divjak et al., 2022a). Historically the OULDI approach was developed for educators to map their own course (Conole, 2012; Conole et al., 2008), and not necessarily how the modules and LOs were aligned with the wider curriculum as before 2012 most OU students followed individual modules rather than following a full degree. With the introduction of the new fee system in the UK in 2012 that primarily rewards universities when students complete their degrees (rather that individual modules) some efforts have been made to ensure that LDs are more aligned across a qualification, but this is not necessarily visible in the OULDI functionality. Therefore, University of Zagreb, FOI identified a need to develop an approach that also provided vertical alignment of LOs at the study program level with those at the course level, in line with the principles of the Bologna Process (2003) and the European Qualifications Framework (EQF: European Parliament and Council of the European Union, 2017).

In the problem investigation design cycle, Divjak et al. (2022a) explored several LD approaches and combined the ABC LD approach of Laurillard et al. (2013) and the OULDI. The two approaches provided a valuable input for the development of some aspects of the BDP concept and tool, however, the new BDP concept and tool also aimed to introduce a certain level of innovation at the level of course LD and curriculum LA. The BDP tool provides analytics of course LD, which can be used to further improve the LD. Moreover, the BDP tool introduces an innovation in terms of linking courses with the study program learning outcomes, as well as the prioritization of learning outcomes. This enables curriculum analytics in the LD phase which takes into account the study program level perspective, as well as covering learning outcomes with meaningful teaching and learning activities (TLA). This can inform curriculum-related decision-making among program managers and directors (Ochoa, 2016). As illustrated in Fig. 3.4, as well as providing vertical alignment on a macro level the BDP tool also allows for horizontal alignment of intended LOs on a course level with TLA on a micro level. As another aspect of innovation, the BDP concept and tool enable the planning of four different modes of delivery (f2f, online, blended, hybrid), which was not the case with the other two approaches.

On the micro (course) level, as presented in Fig. 3.5, the concept links course LOs with specific topics. Every topic is linked with units, each divided into activities, which are assigned with descriptors, including the TLA type (based on the ABC and OULDI approach) and student workload (also a part of the OULDI approach). When reviewing the six learning activity types of the ABC approach with the seven learning activity types of the OULDI approach a conscious decision was made in the BDP to combine the learning activity types into six types of teaching and learning activities (i.e., acquisition, discussion, investigation, practice, production, assessment). In the BDP tool, to enable easier visual recognition, each TLA typed is marked with a different colour. Only the ABC LD approach included *collaboration*, whereas only the OULDI included *assessment.* In the BDP concept and tool, *collaboration* was not introduced as a separate TLA type, but rather as a

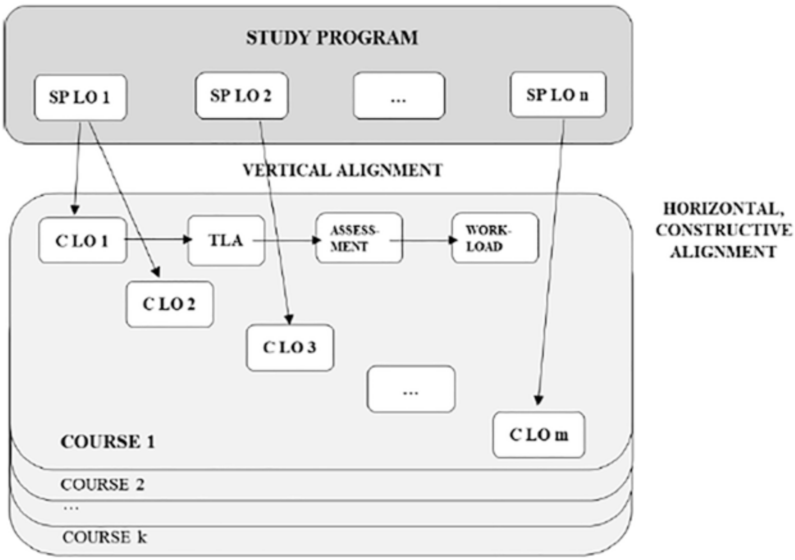


Fig. 3.4 BDP concept: macro level. (Study Program and Course Learning Outcomes). (Source: Divjak et al. (2022a))

horizontal category, which can be indicated for a TLA of any type. Moreover, assessment was included in the BDP tool as a separate TLA type. It primarily refers to *summative assessment,* as *formative assessment* can be a part of other TLA types (e.g., discussion, practice, investigation). In such cases, the BDP tool enables an indication of *formative assessment* as a part of TLAs of other types.

In the treatment design cycle, a range of approaches were explored and tested. The BDP approach also provides possibilities for analysis of a planned LD, focusing on curriculum LA. The LA dashboard gives an overview of the entire study program with attached courses, and it also provides support to educators in reflecting on their LD planning. The BDP approach enables to establish whether study program LOs are covered by course LOs. It also provides analyses of modes of delivery, TLA types, and horizontal descriptors such as collaboration and assessment.

This is illustrated by the LD of a MOOC called Teaching entrepreneurial competences, developed within the eDesk Erasmus+ project in Fig. 3.6. Educators can describe their LOs and provide specific weights in terms of how much workload is expected from learners addressing these LOs. Figure 3.7 illustrates an example of a Planning page which allows educators to create topics and units. This view presents an overview of topics that can be rearranged at any time by any of the educators co-creating the MOOC, and for each topic educators can see the learners' workload in hours. Finally, a unique feature of the BDP approach is the advanced LA dashboard that allows educators to directly explore their design decisions. While in the OULDI approach a lot of manual activities are done and checked by educators and the LD team (Toetenel & Rienties, 2016), a main benefit of the BDP approach is the

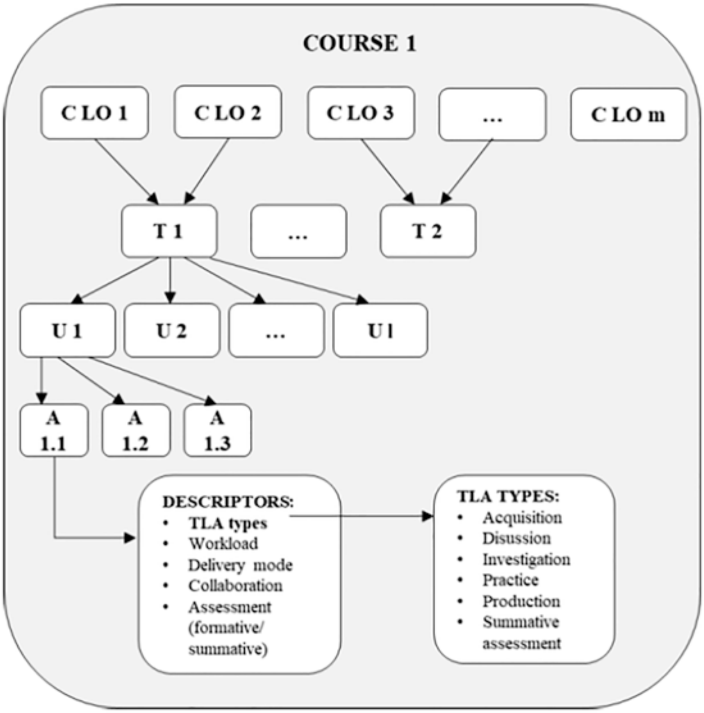


Fig. 3.5 BDP concept: micro level. (*C LO* course LO, *T* topic, *U* unit, *A* activity). (Source: Divjak et al. (2022a))

automatic generation of potentially useful visualisation data and analyses of LD decisions made by educators. Figure 3.8 shows detailed information for a single unit. Each unit consists of one or more TLAs. The order of activities can also be rearranged, and educators can set properties for every activity such as delivery mode (i.e. f2f/blended/online), workload, type of activity (acquisition, communication, etc.), presence of an educator, feedback provider (if applicable) as well as indicate whether the TLA serves as formative or summative assessment (e.g. see Fig. 3.9).

3.4 Initial Treatment Validation Experiences

While substantial work is currently in process to design, test, explore, implement, and validate the BDP approach, the preliminary explorations of the BDP approach across 64 practitioners from ten institutions from nine countries seem positive (Divjak et al., 2022a). At this point three cycles of iterations have been explored. In the first validation cycle, the first version of the BDP approach (v1.1) was presented at an international workshop organized within the RAPIDE project, held at the

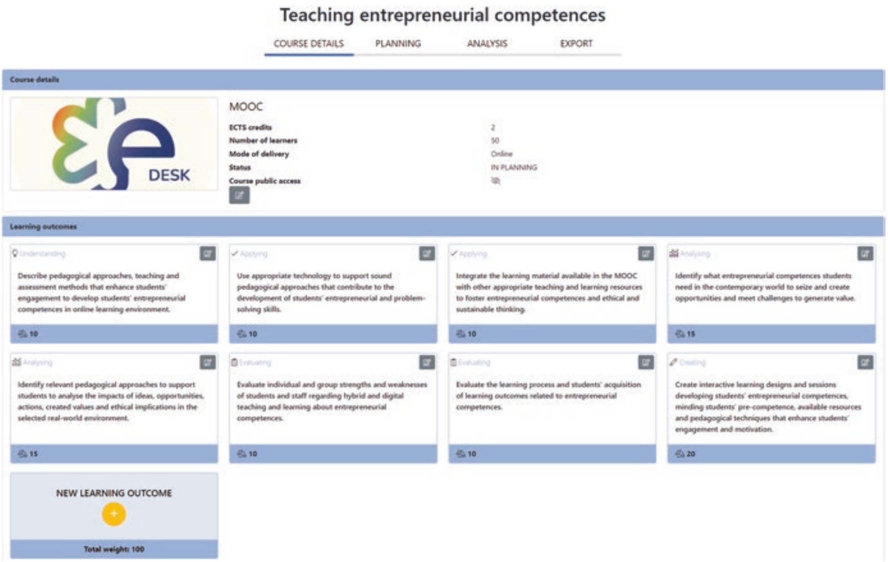


Fig. 3.6 Course details with learning outcomes. (Source: BDP tool and eDesk)

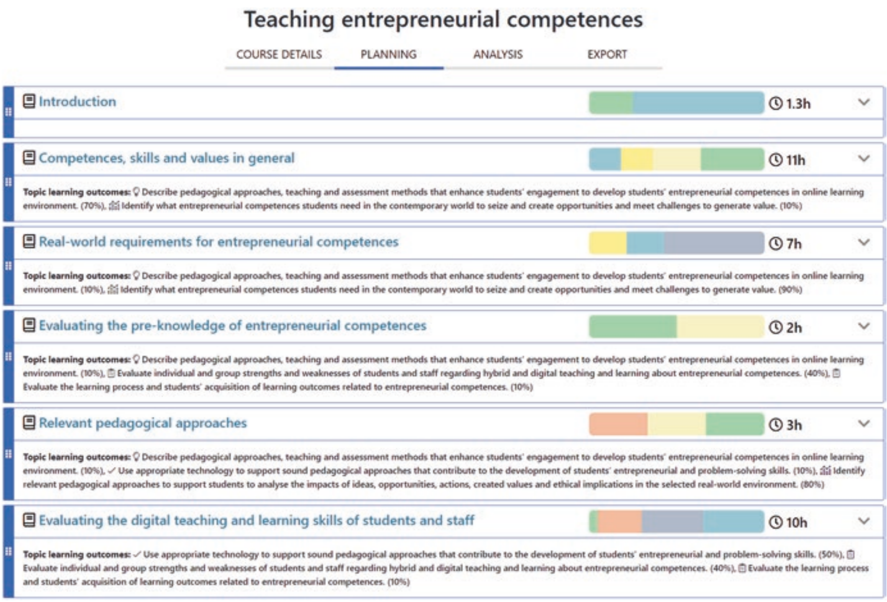


Fig. 3.7 List of course topics. (Source: BDP tool and eDesk)

beginning of September 2021. The workshop was attended by 30 practitioners (HE teachers) from five universities in four countries (Croatia, Germany, the Netherlands, the UK). Practitioners were given a task to plan courses in the BDP tool and then

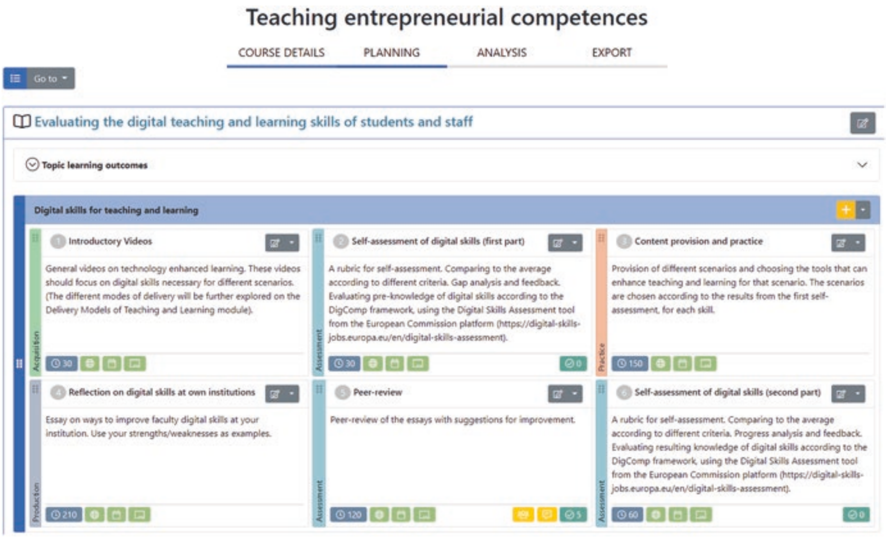


Fig. 3.8 Units and teaching and learning activities for specific topic. (Source: BDP tool and eDesk)

report on their experiences. As indicated by (Divjak et al., 2022a, p. 10), "[p]ractitioners reported a highly positive feedback in terms of the usefulness of the tool and its applicability in their contexts. However, they also provided valuable feedback in terms of further improvements".

In the second cycle, version v1.2 was validated at an international workshop within another EU Erasmus+ project Teach4Edu aiming at accelerating the transition to education 4.0 in HEIs, held later in September 2021. The workshop was attended by 22 practitioners from seven universities in seven countries (Croatia, Estonia, Italy, Serbia, Slovakia, Spain, the UK). Here, the BDP approach is used to build courses to be implemented in collaboration between the participating universities. Again the feedback was positive, but included several suggestions for further development of the BDP approach (Divjak et al., 2022a). For example, a stronger emphasis on vertical alignment, linking LOs with national or international qualifications frameworks (e.g., the EQF) would be appreciated by participants. Another suggestion was to integrate the BDP approach with a learning management system (LMS), especially in tracking students' progress. This would make a lot of sense, as a lot of studies have shown that embedding LD decisions in LMS provide useful LA data for both educators and students (Nguyen et al., 2017, 2018a; Viberg et al., 2018; Herodotou et al., 2020). Finally, as indicated by (Divjak et al., 2022a, p. 10) "[p]articipants were highly appreciative of the constructive alignment between LOs and assessment activities, stressing the importance of clearly linking LOs with concrete assessment tasks in LMSs".

In the third cycle, 14 computer science educators from four institutions from four countries (Croatia, Italy, Serbia, Slovenia) joined a hybrid event hosted by University of Belgrade, Serbia, as part of the Teach4EDU project in February 2022. By

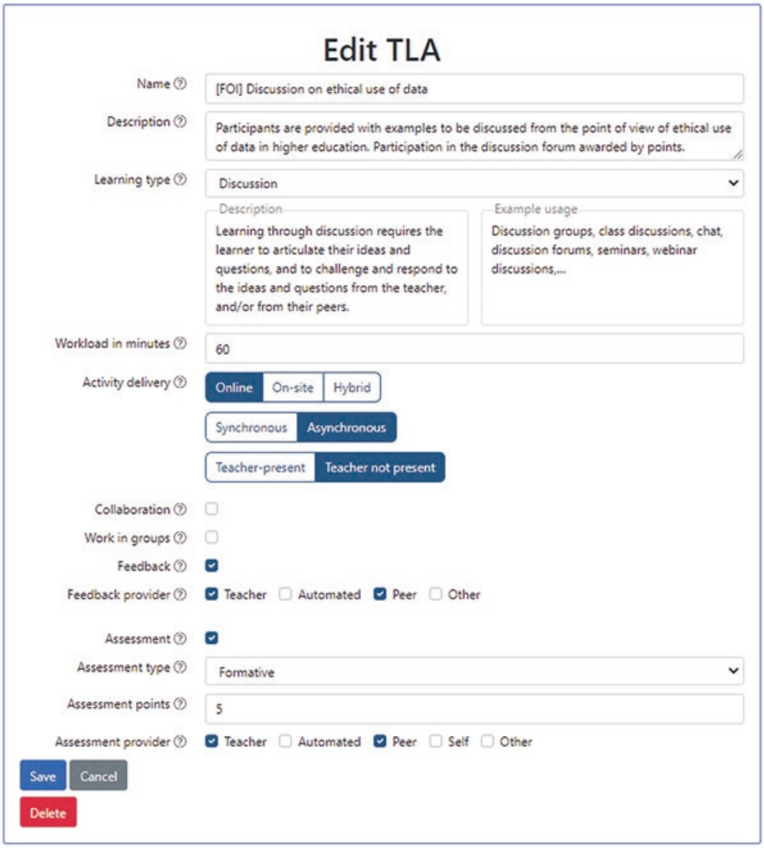


Fig. 3.9 Description of a TLA (Source: BDP tool and RAPIDE)

working on so-called Joined Creative Classrooms (JCCs) educators worked on co-designing seven JCCs that will be implemented in 2022/2023. JCC stands for a course that is planned and carried out between teachers from different institutions and involves students from different countries and institutions. Teaching and learning modality (online, onsite or hybrid) is agreed between teachers and is flexible from course to course. The same is with the course duration, number of credits, and learning activities. The piloting of such concept will highlight the effective ways to implement such combined efforts and might reveal possible templates for computer science courses in respect to their LD.

Using the BDP platform in combination with Zoom, educators worked together on fine-tuning and finalising their respective LDs for their JCC. Additional advantage of the platform lies in the fact that teachers are able to set which activities will be conducted online, for which of the activities the teacher needs to be present, duration of the activities, etc. Those features are extremely useful when planning a collaborative effort of several teachers and to plan onsite versus online classes that

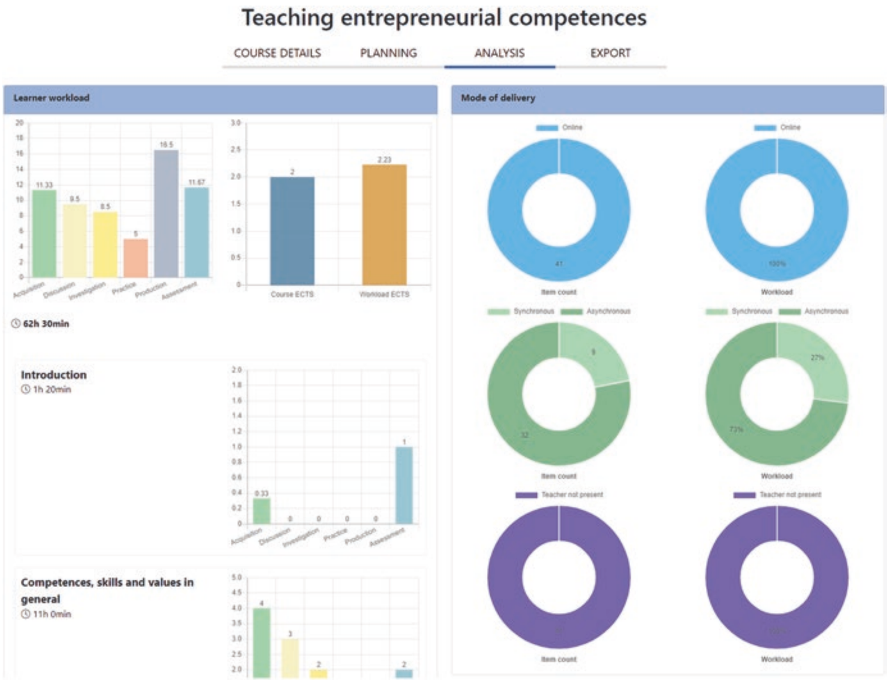
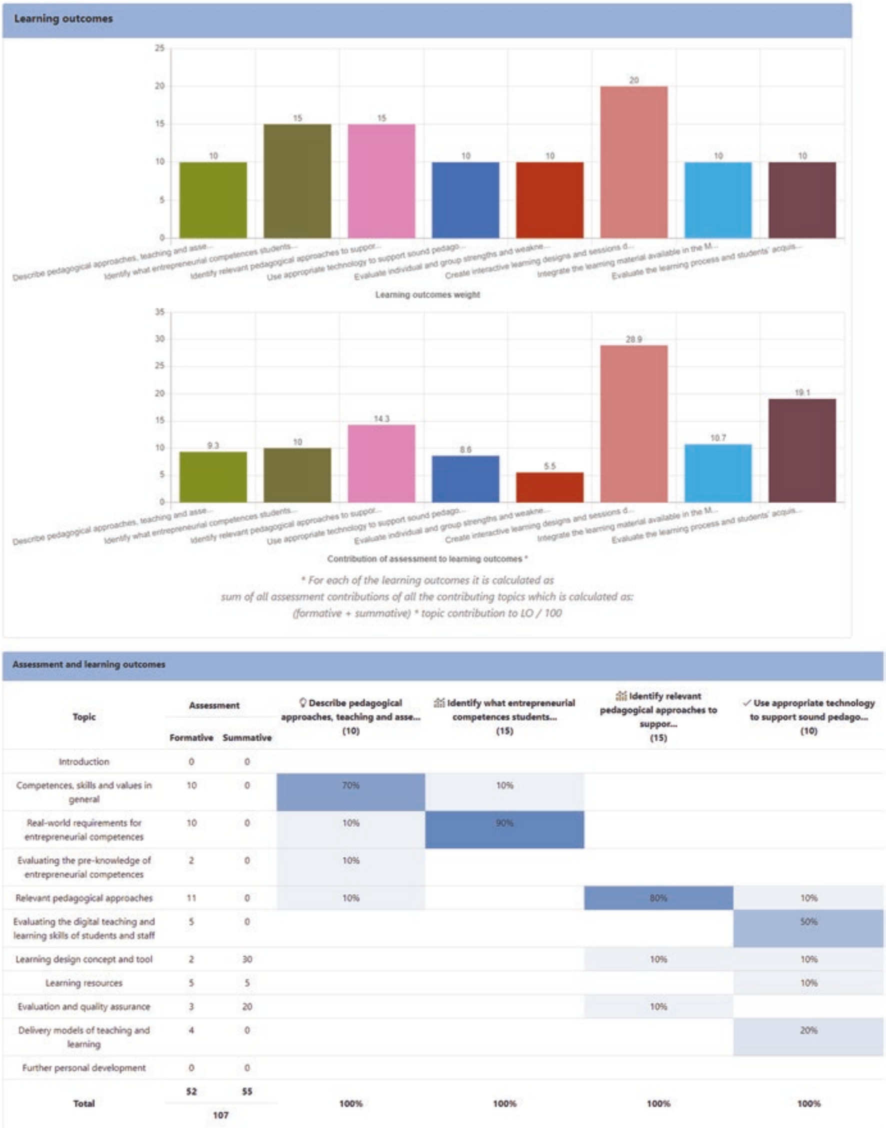


Fig. 3.10 Learning design analysis for specific course

need to be taken among students from different countries but within the same course. Educators also reported the ease of use of the platform and the usefulness of dashboards that helped them to fine-tune the existing activities to match one of the three predefined LD templates specific to Education 4.0 and computer science courses that were given to them outside of the platform (Balaban et al., 2021). LD templates are coined to reflect one of the three broad ways to distribute learning activity types. Once the LD templates are refined based on the feedback after the end of the pilots, those will be implemented into the BDP platform, and the educators will be able to compare their current LD to one of the pre-selected templates (Figs. 3.10 and 3.11).

3.5 Discussion

The primary goal of this chapter was to explore what we have learned from refining one widely used Learning Analytics (LA) and Learning Design (LD) approach from one institution to a different context/country/culture. As evidenced by a range of studies (Dawson et al., 2018; Tsai et al., 2020; Viberg et al., 2018; Wasson & Kirschner, 2020), few institutions have implemented LA at scale, and even fewer



Topic	Assessment		Describe pedagogical approaches, teaching and asse... (10)	Identify what entrepreneurial competences students... (15)	Identify relevant pedagogical approaches to suppor... (15)	Use appropriate technology to support sound pedago... (10)
	Formative	Summative				
Introduction	0	0				
Competences, skills and values in general	10	0	70%	10%		
Real-world requirements for entrepreneurial competences	10	0	10%	90%		
Evaluating the pre-knowledge of entrepreneurial competences	2	0	10%			
Relevant pedagogical approaches	11	0	10%		80%	10%
Evaluating the digital teaching and learning skills of students and staff	5	0				50%
Learning design concept and tool	2	30			10%	10%
Learning resources	5	5				10%
Evaluation and quality assurance	3	20			10%	
Delivery models of teaching and learning	4	0				20%
Further personal development	0	0				
Total	52	55	100%	100%	100%	100%
	107					

Fig. 3.11 Alignment of assessment and learning outcomes

have tried to share and adopt their approaches to different institutions contexts. In this chapter we reflected on the lessons learned from adopting this approach into three aspects of the Balanced Design Planner (BDP) approach (i.e., concept, dashboard, tool), which were developed and tested with 64 practitioners from ten institutions at nine countries in 2021/2022.

As illustrated in this chapter, building on two established LD approaches of OULDI (Conole, 2012; Rienties & Toetenel, 2016) and ABC LD approach (Laurillard et al., 2013) the BDP approach aimed to support a balanced LD planning for educators who mostly work in universities that before COVID-19 primarily taught f2f, enabling the planning of four different modes of delivery (f2f, online, blended, hybrid). The BDP approach enables purposeful implementation of innovative digital pedagogies, including teaching, learning and assessment, and stimulating engagement of both students and teachers. As indicated by the preliminary work with the practitioners the initial experiences with working with the BDP approach seemed positive. Most participant educators indicated that the BDP approach was easy to use, and helped them to construct and visualise their LD ideas and concepts. In particular when educators were co-designing a learning unit or even a whole course together across two or more universities the BDP approach was appreciated, in particular the automatic LA visualisations.

While the initial steps seem promising, more work needs to be done in order to determine whether the initial design plans co-constructed by these 64 practitioners actually lead to powerful LDs that meet diverse students' needs. The first courses using the BDP approach are currently in the implementation phase and we hope to obtain initial student reactions and possibly LA data before the summer of 2022. Furthermore, more work needs to be done in terms of the horizontal and vertical alignment of the BDP approach, as well as accessibility testing to make sure that the approach is appropriate for users with different learning and accessibility needs. Perhaps the Pandemic has also accelerated the awareness of educators to build on their (often first) online teaching and learning experiences and to provide a clear pedagogical structure to their LD.

A next crucial step in validating any LD approach is testing them in authentic learning environments, virtual and blended, as well as face-to-face teaching and learning, to test whether they provide effective support in implementation of innovative pedagogies. Whether or not this approach is appropriate and effective in each of the participating institutions and countries needs more work, and perhaps glocalisation of respective approaches. Furthermore, LD approaches are not reserved only for HE or MOOC development. Sound LD should take a prominent place in pretertiary education as well as in industrial environment for LD of training of their employees and customers.

Finally, future research should explore how LD approaches can make full use of LA in enhancing LD planning, and support innovative pedagogies (Divjak et al., 2022a), but also to link LD approaches with LMSs in order to check the implementation of LD in authentic teaching and learning environments, by means and approaches of LA. Sound LD based on LOs, as well as link to LMS that encompasses learning and assessment data could be valuable bases for microcredentials and digital credentials in general.

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Chapter 4
Learning Dashboards for Academic Advising in Practice

Tinne De Laet

4.1 Introduction

This section sets the scene by discussing academic advising, advising analytics, and the advising context at KU Leuven, the higher education institute at which the advising analytics was put into practice.

4.1.1 Academic Advising

When studying in higher education, students can encounter difficulties in pursuing their academic goals. These difficulties range from struggling with academic integration, not finding an appropriate study approach, not making progress as planned, not being able to make decisions regarding their study career, a mismatch between their personal goals and the academic progress regulations, but also personal challenges related to mental health and their financial or home situation. Academic advisors are often the first point of contact for students inside the higher education system if such challenges are encountered. Academic advising should focus on getting a clear picture of students' life and career goals, contexts, and difficulties, trying to align students' needs and goals with the academic context, and jointly identifying possible academic plans or next steps to take. Students typically consult an academic advisor when they are confronted with sudden difficulties such as disappointing academic progress, when they are facing study progress measures, or

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when they have to take academic decisions such as choosing a bachelor or major. Academic advising often occurs in advising dialogues, personal face-to-face meetings either physically or digitally between the student and their advisor. Strong academic advising practices have been shown to have a positive impact on retention and persistence (Pascarella & Terenzini, 2005; Tinto, 1993; Drake, 2011; Drake et al., 2013; Braxton et al., 2014; Sharkin, 2004; Young-Jones et al., 2013; Bahr, 2008). Academic advising has been identified by students as a key aspect of their educational experiences, and Samuels (2016) showed that the commitment of higher education institutions to academic advising relates to their commitment to student success. In most higher education institutions academic advising programs are established, also reflected by specific criteria accreditation agencies such as ABET define and evaluate.

4.1.2 Towards Advising Analytics

Stoneham (2015) states that a data-based approach to academic advising has gained interest over the last decades, both in the research communities of educational recommender systems (Drachsler et al., 2015), educational data mining (Papamitsiou & Economides, 2014), learning analytics (Duval, 2011; Siemens & Baker, 2012), and academic analytics (Campbell et al., 2007). This work is rooted in the learning analytics tradition, defined by Duval (2011) as "collecting traces that learners leave behind and using those traces to improve learning". When combining learning analytics with visualisation, one comes to the domain of learning analytics dashboards. Learning analytics dashboards are visual displays of educational traces, which can be descriptive in nature but can also be supplemented with outcomes of educational data mining and predictive or prescriptive analytics, presented to end-users such as teachers, learners, or in our case academic advisors. The majority of learning analytics dashboards related to academic advising focuses on the identification of students at risk (Calvert, 2014; Choi et al., 2018; Herodotou et al., 2019; Wolff et al., 2014; Essa & Ayad, 2012). In the last 5 years, research has also focused on how learning analytics dashboards can support advising dialogues (Gavriushenko et al., 2017; Okewu & Daramola, 2017; Fiorini et al., 2018; Gutiérrez et al., 2020; Guerra et al., 2020; De Laet et al., 2020; Charleer et al., 2018; Millecamp et al., 2018). The proliferation of commercial learning analytics tools and their incorporation into advising practices however seems to go faster than the development of research evidence on academic advising analytics (Gutiérrez et al., 2020; Jones, 2019). The impact of dashboards supporting the advising dialogue has been observed in the insights generated during advising conversations both for advisors (Charleer et al., 2018) and students (Millecamp et al., 2018), the exploration of different academic scenarios (Gutiérrez et al., 2020), the advisors' perceived level of support (De Laet et al., 2020), and the level to which students follow an advised study plan (De Laet et al., 2020), while evidence of impact on academic achievement or retention is still missing.

Scaling learning analytics practices to institutional scale and incorporating learning analytics in educational practices is extremely challenging as scaling requires investment, overcoming resistance to change, alignment with educational values of the higher education institute, and tailoring to the particular context (Broos et al., 2020). In an effort to better understand the challenge of scaling up learning analytics applications to an institutional scale both the technology acceptance model (Davis et al., 1989) and academic resistance models (Piderit, 2000) have been used. The incorporation of learning analytics into advising practice has shown to have its particular challenges. Usability issues are paramount, but these are considered to be quite readily solvable. Contextualisation is challenging but manageable if handled with proper care, time, and investment (Guerra et al., 2020; Ahn et al., 2019). A more profound challenge is related to the apparent mismatch between institutional leaders' expectations of learning analytics gains (reduce drop-out, decrease time to graduation, identify students at risk, rationalise educational programs and student academic pathways, etc.) and the particular values and practices of academic advisors (knowing their students' goals, contexts, personal difficulties, identifying individualised academic trajectories tailored to student goals, etc.), as identified by Jones (2019).

4.1.3 KU Leuven's Advising Context

The chapter focuses on academic advising at KU Leuven in Belgium. KU Leuven, founded in 1425, is a highly ranked research-intensive and general university. The university offers education to more than 45.000 students in 48 bachelors and 138 masters programs, organised in 15 faculties and 13 campuses spread over Flanders, the Dutch-speaking part of Belgium. KU Leuven has an open-admission policy, allowing every student with a Flemish or Dutch secondary education diploma to enrol in any bachelor program (except medicine and dentistry). This entails the risk that students choose a study program for which they do not have the appropriate knowledge, skill set, or motivation, resulting in typical drop-out rates of 40%, and ahigh level of heterogeneity in student background within a single program (Pinxten et al., 2017).

The particular focus of this chapter is on advising first-year students (Sect. 4.2) and aspiring students (Sect. 4.3) at KU Leuven. Advising is done by faculty-based academic advisors who are typically employed as educational support staff. The academic advisors most often have a degree from the program they are advising for, and receive additional training on academic advising from central university services. They are experts in the current organisation of the program and the regulations, both program-specific and university-wide, and have the required skills to offer professional advising dialogues. Furthermore, academic advisors are typically part of the program advisory committees, often advise the program directors, and are responsible for handling and approving the individual study program of students. Actual advising practices and adviser-student ratios differ between faculties and programs due to the differences in the educational context (e.g. programs with high dropout versus programs with very selective entrance exams) and staff context (advisor-student ratio, and what tasks staff has to combine).

4.2 Institution-Wide Advising Dashboard

This section reports on the journey of the development of an institution-wide advising dashboard, called LISSA, acronym for "Learning dashboard for Insights and Support during Study Advice". First, Sect. 4.4.1 elaborates on the development and piloting of LISSA. Next, Sect. 4.4.2 and Sect. 4.4.3 share experiences of scaling up the dashboard to an institutional level and embedding it into institutional processes and practices.

4.2.1 LISSA, Pilot of a Descriptive Advising Dashboard

Within the context of the European project ABLE (See acknowledgement) LISSA was conceived to support the dialogue between academic advisors and students, following an intensive user-centred design methodology supported by a rapid-prototyping design approach (Charleer et al., 2018; Millecamp et al., 2018). Charleer et al. (2018) reported on the design process and evaluation of the first version, which was developed in close collaboration with five academic advisors, two visualisation experts, and a researcher on academic advising and student success. The stakeholders were involved in the different steps of the design through observations of actual advising sessions, brainstorms, and semi-structured interviews connected to dashboard mock-ups and functional dashboards. An important premise of the project was to only use data that is or could be readily available at any higher education institute, i.e. academic data on student progress. LISSA is based on a story-telling approach, allowing the academic advisor to focus on key moments of the student's academic career by providing an overview of every key moment in chronological order up until the period in which the advising sessions are held (Fig. 4.1). LISSA only uses descriptive analytics and visualisations and contains no predictive or prescriptive components.

As shown in Fig. 4.1, LISSA provides a column with an overview of the obtained grades for each academic period, hereby using colour coding (green indicates the student passed the course (≥10/20), orange means that the student mildly failed the course (8 or 9/20), whereas red indicates a grade lower than 8/20). When an advisor clicks on a course, a histogram of course grades is shown (Fig. 4.1c). At the top of each column, an overview of the global progress (obtained ECTS credits) is provided. LISSA also includes the evolution of the student's global progress, measured as the global study efficiency, over the different academic periods and compared to

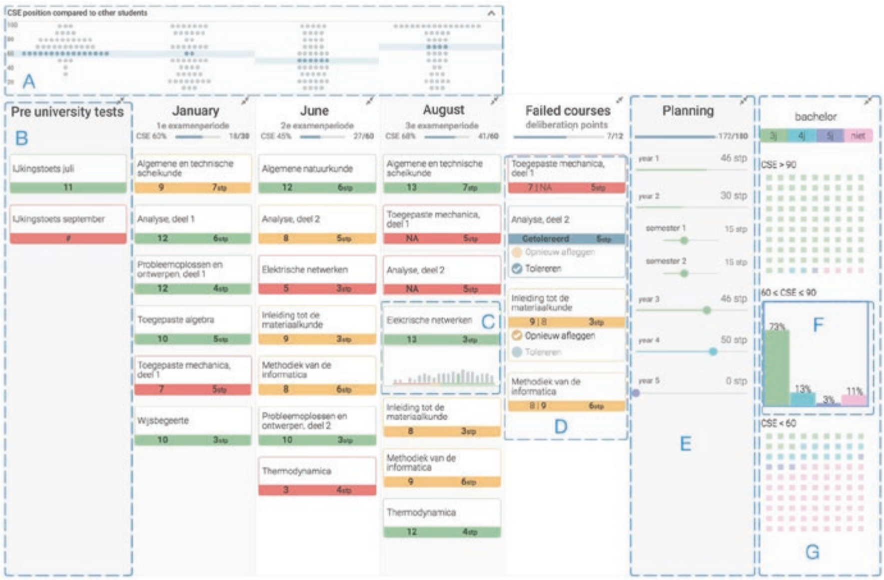

Fig. 4.1 Final design of the LISSA dashboard in the pilot project, version for the end of the academic year. From left to right: (**a**) Histogram showing the performance of peers for each key moment. (**b**) Column for an academic period containing the obtained grades during that period, and if applicable with the summarising academic progress in terms of study efficiency at the top. (**c**) Histogram of peer performance for a course, shown when triggered by an advisor. (**d**) Overview with all failed courses and the option to simulate the "toleration" of these courses. (**e**) Planning module to plan the study load over the remaining years of the program. (**f**) Histogram of study trajectory of previous students with a similar profile. (**g**) "bachelor" showing the relation between the study progress in the current academic period and the number of years needed to finish the program based on historic data. (Figure from Millecamp et al. (2018))

the peers in the program (dotted histogram where each dot represents two percent of the students in the same program, Fig. 4.1a). In the rightmost module "bachelor" (Fig. 4.1g), the relation between the study efficiency in the current academic period and the number of years needed to finish the program are visualised using data from previous student cohorts. The visualisation divides students into three different groups based on the current study efficiency. For each of these groups, it is shown which proportion of students did not obtain the degree, or obtained it in respectively 3, 4, or 5 years. If the advisor hovers over a particular group, the visualisation is converted into a bar chart (Fig. 4.1g). The dashboard offers additional modules, depending on the particular academic period. In the example provided, two additional modules are shown. The first, 'Failed courses' (Fig. 4.1d), provides an overview of the courses that a student failed and can potentially "tolerate", including a simulation of the "tolerating" process. The second, Planning (Fig. 4.1d), provides a simple module to support the advisor and student in planning the remaining number of credits required to obtain the degree over the next academic years. The academic advisor determines which components are visible in the LISSA dashboard during a particular advising dialogue. Upon loading of the dashboard, the additional modules (Fig. 4.1ag) are all 'collapsed', but they can be readily opened by the advisor if he/she wants to use the module within the advising dialogue. The code of the LISSA dashboard, developed using D3.js (https://d3js.org/) and Meteor (https://www.meteor.com/) is available as open source on GitHub (https://github.com/svencharleer/stbd).

The focus of the pilot was strongly on delivering a dashboard that is scalable on the one hand but still answers to the particular needs of academic advisors on the other hand. This resulted in a balancing act naturally influenced by the quantitative indicators of the European project that supported the development of LISSA. Two particular examples illustrate this balancing act.

- The *data* underlying LISSA was mostly available within the central data warehouses of the university for all programs (grades, global study progress, graduation time). The university uses a semester-based system, which results in three main academic periods: first semester, second semester, and re-examinations in summer. Academic advisors found that LISSA would be more valuable if additional testing periods could be included such as the results of pre-university tests (Fig. 4.1b) and intermediate tests in the first and second semesters. The data of these additional tests are however not available in the university's data warehouse. To support the inclusion of this additional data, a dedicated infrastructure was built that allows academic advisors to upload the data.
- The *global study progress thresholds* that define the three groups in the rightmost "bachelor" module (Fig. 4.1g) are program specific. Conversations with the different programs and data analysis of study progress in different programs showed that despite the fact the same global study progress regulations hold within all programs of the university, the relation between global study progress in a particular exam period and graduation time differs substantially between programs. Therefore, university-wide progress thresholds could not be obtained and program-specific thresholds needed to be defined. To support programs in the definition of their program-specific thresholds a separate application was built and a procedure was set up to upload these thresholds to the data warehouse underlying LISSA.

Millecamp et al. (2018) shares the experience of piloting LISSA in 26 programs within KU Leuven, reaching more than 4000 students and 120 academic advisors. Written documentation supported the academic advisors in using the LISSA dashboard. The documentation focused, besides the required technical information, on the goal and underlying philosophy of the dashboard and an explanation of the underlying data and visualisations. From the LISSA development phase and pilots it was found that LISSA was very well received by advisors and students (Charleer et al., 2018; Millecamp et al., 2018), supported personal advising dialogues (Charleer et al., 2018), helped to motivate students (Charleer et al., 2018), provided fact-based evidence on the side (Charleer et al., 2018), supported the narrative thread and personalisation of the dialogue (Charleer et al., 2018), and triggered factual, interpretative, and reflective insights during these dialogues both for advisors (Charleer et al., 2018) and students (Millecamp et al., 2018).

4.2.2 Towards an Institution-Wide Advising Dashboard

As Sect. 4.4.1 showed the LISSA dashboard was piloted at a large scale within KU Leuven. The pilot showed that LISSA was strongly supported by academic advisors and students. Strengthened by this successful experience, conversations were started with the policymakers of KU Leuven to continue the LISSA dashboard and embed it in actual university practices and processes. These conversations showed that while KU Leuven policymakers were supportive of the dashboard, no immediate mechanisms were available to start the process of scaling and embedding. KU Leuven policymakers recognised that other innovative educational projects met similar struggles in their long-term continuation and scaling to the institutional level. In a new policy round KU Leuven included a new priority called "Going Digital" aimed at strengthening the use of educational technology within the institute. The "Going Digital" priority named ten short-term goals, including the scaling of LISSA to the institutional level. In support of the policy plan, a strategic plan was developed that supports educational technology projects in three phases: (1) the innovation phase to stimulate innovative bottom-up initiatives, (2) the scaling-up phase, relying on a strong collaboration with institutional services (IT, educational policy, student services, educational support services, etc.) to analyse if and how the best bottom-up initiatives can be scaled up, and (3) the actual upscaling and anchoring of the initiatives. LISSA was selected for the scaling-up and anchoring phase.

A multi-disciplinary project team was established to support the scaling of LISSA, consisting of the coordinator and researchers of the LISSA pilot project, the coordinator of KU Leuven Learning Lab (central KU Leuven centre for educational support and development), the coordinator of KU Leuven's central study advice centre, the coordinator of the data management unit, different coordinators of IT-teams of KU Leuven's IT centre, a student representative, and an academic advisor. Other colleagues were added ad-hoc depending on the phase and the needs of the scale-up. The task of the scale-up consisted of:

- acquiring the required policy support and establishing a *policy* around learning dashboards (using workshops with stakeholders and presentations to program committees, councils, working groups, etc.),
- exploring if and how LISSA could be integrated with the *IT infrastructure* institution-wide,
- exploring if and how LISSA could be integrated within the KU Leuven *practices and processes of academic advising.*

In the scale-up process the most notable points of discussion were:

- *Technology to be used:* While the LISSA-pilot was available as open source and was fully functional, its underlying technology did not match the typical technology used and expertise available within KU Leuven IT department. It was therefore decided to re-implement the dashboard within technology that KU Leuven was already being used for reports of (educational) data in the institution's data warehouses targeting university staff: SAP Business Objects Business Intelligence suite (https://www.sap.com/products/bi-platform.html). Hereby, one could build on in-house expertise, existing connections with the data warehouses, and very importantly security and authentication granting access to particular staff roles at KU Leuven only. On the downside, SAP Business Objects Business Intelligence suite is not optimised for interactivity, requiring to make compromises regarding the user interface, which in particular resulted in modules being spread over different pages rather than being integrated into one dashboard that can be observed at a glance.
- *Level of customisation for programs:* As explained in Sect. 4.4.1 the LISSA pilot dashboard offered customisation for programs, by allowing programs to upload additional data for additional testing periods such as intermediate tests or pre-university tests not available in KU Leuven's data warehouses, and custom global study progress thresholds for the "bachelor" module of the dashboard (Fig. 4.1g). The lack of culture, experience, and procedures of the central IT-service to allow for program-specific data and customisation of reports clashed with the findings of the pilot that customisation was key. The scaling team recognised the necessity of customisation and established new processes to allow for it.
- *Professionalisation of academic advisors around data-supported advising:* To provide proper support for the academic advisors to use the advising dashboard, and ensure that the dashboard is used within the institution's vision around advising, it was decided that training had to be developed and that completing this training would be mandatory to gain access to the dashboard.
- *Workload of academic advisors:* Some academic advisors expressed the fear that using the dashboard would increase their workload, make the advising conversations lengthier, and that the use of LISSA would be mandatory for every advising dialogue. Interestingly, similar concerns have been highlighted by Jones (2019) in other institutions using advising analytics. The project team decided that as LISSA was designed to be supportive of the advising dialogue, academic advisors themselves should decide if, how, and with which goal LISSA is used in a particular advising dialogue.
- *Privacy and ethics*: Notably, there was little discussion around privacy and ethics of the dashboard. Potential reasons are that LISSA does not disclose more data to academic advisors than before (but just in a more convenient format), does not use any sensitive personal data of students (gender, scholarship status, pioneering status, etc.), limits itself to descriptive analytics and does not include any prescriptive or predictive analytics, which is typically found to trigger more discussion (Jones, 2019), and were most importantly in the hands of academic advi-

sors who are professionally trained for advising conversations and had the freedom to decide if, how, and with what goal LISSA is used.
- *Establishing new processes and responsible teams:* Long-term embedding of LISSA requires that responsible teams are assigned and processes are established, not only for the maintenance of the dashboard but also for the professionalisation of academic advisors, the processes to gather and include program-specific data, etc. Identifying these teams and assigning them particular responsibilities is a non-trivial task in a higher education institution where staff already experiences a high workload at all levels.

Interestingly the scaling of LISSA had an influence beyond the scope of the advising dashboard itself:

- *Professionalisation around data-supported advising:* The practice of data-supporting advising, and not only the LISSA dashboard, was included in the professionalisation of academic advisors.
- *Discussion around learning analytics:* The LISSA dashboard was a first institution wide implementation of learning analytics and helped to start the discussion of a general policy around learning analytics supported by the SHEILA framework (Tsai et al., 2018; Broos et al., 2020). As supported by the recommendation of Broos et al. (2020), this policy development was found to be supported by the specific example of LISSA, rendering the conversations less abstract and more tangible. The policy discussion will pave the way for the further inclusion of learning analytics applications in educational practice.
- *Opening for program-specific adaptations:* For the first time, KU Leuven established procedures and processes to allow for program-specific educational data inclusion in the data warehouse and program-specific parameters in educational reports/dashboards. This will again pave the way for the future customisation of KU Leuven application to particular needs of programs.
- *Discussion around study progress within programs:* The customisation of LISSA that allows for the inclusion of data of program-specific tests and program-specific study progress thresholds triggered discussion around study progress within programs. Each program advisory committee had to make a deliberate decision regarding which additional data to include (and which data was, therefore, important for getting a useful overview of a student's academic progress), and which global study progress thresholds to set that can split students into low-progress, medium-progress, and high-progress groups. The latter process gave insight to programs on how first-year study progress is related to study duration, to central KU Leuven on how programs choose to communicate about study progress, and provided leverage to better align the communication around study progress with KU Leuven's vision around advising.
- *Experience in scaling-up innovative educational technology projects:* Finally, the scaling of LISSA was the first innovative education project to run through the "scaling-up" phase of the strategic plan of the new "Going Digital" policy, whose experience will shape future scaling-up projects.

4.2.3 LISSA, Embedded in University Technology, Processes, and Practices

The scaling-up project of LISSA (Sect. 4.4.2) resulted in LISSA as an advising dashboard fully embedded within university technology, processes, and practices.

The scaling project resulted in a:

- *Institution-wide advising dashboard:* LISSA is implemented in BI-technology (Figs. 4.2, 4.3, 4.4, and 4.5), and available to all advisors that followed the mandatory training for using the dashboard in advising dialogues. Procedures and processes are established and responsible persons assigned to ensure that LISSA has long-term viability (technological maintenance, procedures for gathering program-specific data, inclusion in tool-set for advising, etc.)
- *Policy around advising dashboard:* A policy and operation framework was established, highlighting the values of LISSA and offering pointers for the use of LISSA, based on the six dimensions of the SHEILA framework (https://sheilaproject.eu/sheila-framework/create-your-framework/overview/). This framework will further support an institution-wide policy on learning analytics.
- *Professionalisation around data-supported advising and use of advising dashboard:* Professionalisation around data-supported advising and use of the advising dashboards were developed and are now part of the professionalisation of academic advisors.

Fig. 4.2 LISSA as an institution-wide advising dashboard: central module with columns for different academic periods containing the course grades, overall academic progress in terms of study efficiency, and positioning within the peer group

Fig. 4.3 LISSA as an institution-wide advising dashboard: "bachelor" showing the relation between the study progress in the current academic period and the number of years needed to finish the bachelor program based on historic data. The cohorts included in are shown on the top right of the dashboard

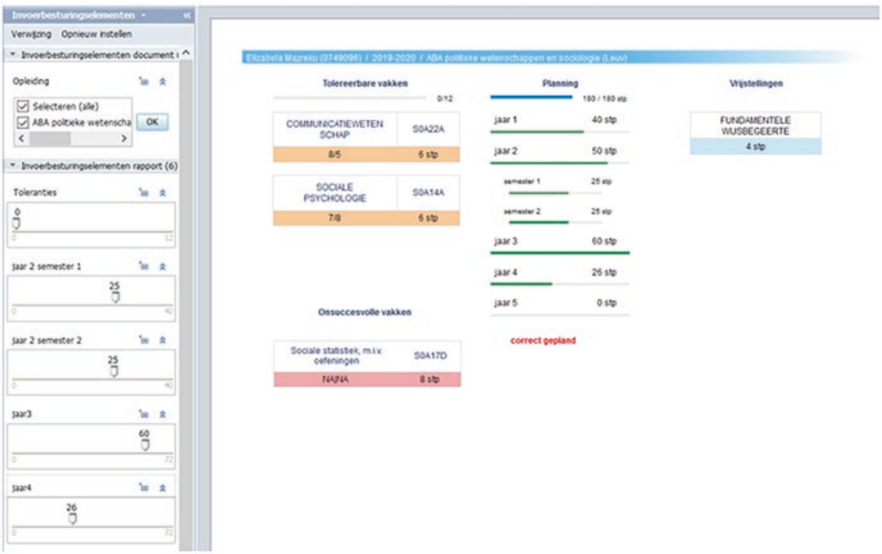

Fig. 4.4 LISSA as an institution-wide advising dashboard: an overview of unsuccessful courses and planning module

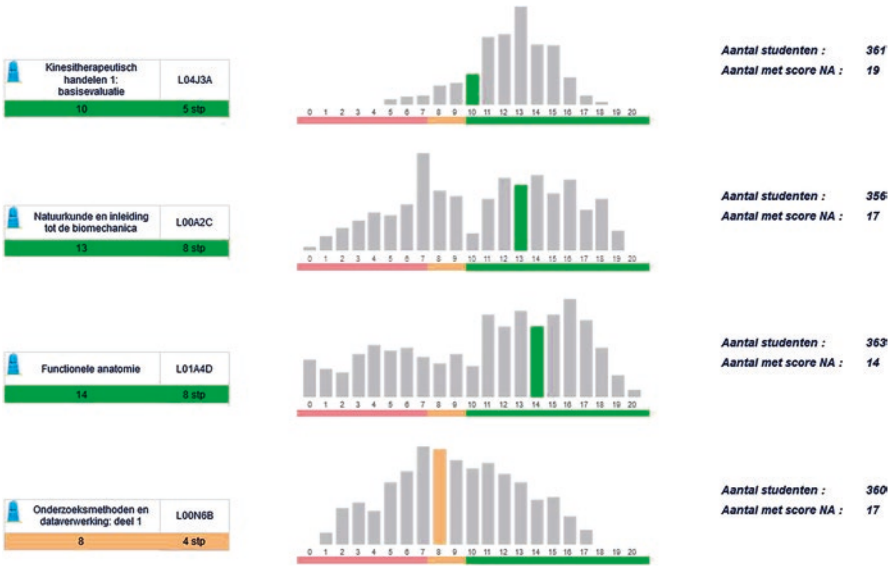

Fig. 4.5 LISSA as an institution-wide advising dashboard: module with histogram for peer performance on different courses

4.2.4 Discussion and Conclusions

This section showed how a bottom-up advising dashboard found its way to institution wide deployment and embedding at KU Leuven. This bottom-up approach supported the development of a dashboard that was well-informed by the particular needs of academic advisors within the particular context of the university and connected to the values of academic advisors within KU Leuven, and the maturity level regarding learning analytics at the institute. As scalability was one of the main drivers from the start of the project, the pilot dashboard already balanced the program-specific needs of academic advisors and the goal to have a university-wide advising dashboard with minimal customisation. While scaling required adaptations, and in particular compromises in the user interface, the main components of the pilot dashboard were successfully translated to a university-wide advising dashboard. The scaling process itself triggered conversations around data-supported advising and learning analytics in general, and allowed to shape KU Leuven's policy around learning analytics with the specific experience of LISSA. The scaling and institutional embedding was only possible thanks to the support provided by KU Leuven's strategic policy "Going Digital" and hereto connected financial stimuli, staff support, and explicit support of university leaders.

Interestingly, the entire process of scaling LISSA contrasts with other experiences of institution-wide advising analytics as reported by Jones (2019). Jones

(2019) reports on the reasons for academic advisors in a higher education institute to reject two academic advising dashboards (Degree Tracker and Student Success Forecast) with prescriptive and predictive advising affordances. The rejection was due to a mismatch between advisors' needs and values (understanding the "whole student", (i.e. a student's unique needs, interests, goals, and challenges, and then offer tailored interventions and support) and administrators needs and values (reduce time to earn a degree, increase retention rates, etc.), which even lead to so-called "contextual suppression", where advisors feel forced by administrators to use dashboards originally developed to support them. Interestingly Jones (2019) reports that the advising technology was observed by advisors to treat a student like a number, while Charleer et al. (2018) reported that LISSA allowed advisors to make the dialogue more personal.

The contrasting experiences of LISSA and Degree Tracker and Student Success Forecast (Jones, 2019) trigger reflection on the differences in the process around and nature of the advising dashboards. First, LISSA does not include any prescriptive or predictive components, while a substantial part of the resistance reported by Jones (2019) is connected to these components. Second, LISSA was the result of a bottom-up project with the goal of supporting the advising dialogue where advisors were included in the iterative user-centred design process (Sect. 4.4.1) resulting in achieving the dashboard's aim to support a personal dialogue, while the advising technology discussed by Jones (2019) was designed to support the achievement of administrators' goals to reduce the time to earn a degree and increase retention. While the goals of advisors and administrators are not necessarily contrasting, it is clear that only a user-centred design process will support the development advising technology that serves the needs of both advisors and administrators. While a user-centred design is intensive time-wise, both cases show that this approach is fundamental towards the acceptance and thus impact of advising analytics (see also the learning analytics process model of Verbert et al., 2013).

4.3 Towards Predictive Advising Dashboards?

LISSA, the advising dashboard deployed institution-wide at KU Leuven, limits itself to descriptive analytics where data underlying student success is visually summarised. While the descriptive visualisations proved to support the advising dialogue, it is unlikely that they can represent the multi-dimensional and complex nature of academic success as it depends on a wide variety of aspects such as students' prior education, current academic achievement, motivation, learning and study skills, intellectual capacity, socio-economic background, and effort level. Predictive models, coming from the domain of Machine Learning (ML), Educational Data Mining, and Learning Analytics (LA) algorithms, have been shown to be capable of including a large set of student and contextual variables to accurately predict student success. This raises the question if and how predictive components can be included in advising dashboards in order to bring the power of predictive algorithms to advising practice.

Predictive models in learning analytics research are wide-spread, but their incorporation and adoption in higher education practice is still challenging due to legal, financial, and ethical considerations. The European GDPR regulation (Regulation 2016/679) and the "right to explanation" in particular are exemplary for the increased awareness around ethical use and privacy. The black-box nature of many predictive models, also referred to as algorithmic opacity (Adadi & Berrada, 2018), challenges this "right to explanation". Algorithmic opacity can furthermore induce mistrust and even suspicion and as a result induce resistance with users and hinder inclusion of predictive algorithm in educational practice. The introduction of predictive analytics in advising practice seems to be particularly challenging (Jones, 2019). When advisors cannot match algorithmic predictions and recommendations with their mental models of student success, they will not trust, and as a consequence not use, the predictive model (Scheers & De Laet, 2021). Advisors can additionally find that predictive algorithms cannot capture the complex nature of student success, ignore the personal situation and individual needs of students, are subject to algorithmic bias, induce self-fulfilling prophecies, and frighten students, or treat students like numbers. Jones (2019) even reported that the predictive advising instruments deployed at an American higher education institute were rejected as advisors found them conflicting with their own values, pointing to a fundamental mismatch.

The fast-maturing domain of XAI (eXplainable AI) aims to make the complex internal mechanisms of predictive models transparent for users (Adadi & Berrada, 2018) and thereby increase understanding or event trust (Spinner et al., 2019). XAI might therefore be instrumental to bring the power of predictive algorithms to advising practice. Adding explanations to predictions can furthermore enhance the understanding of the reality (Doshi-Velez & Kim, 2017; Alamri & Alharbi, 2021), such as the identification of strengths and weaknesses of students in the case of advising, but also the identification of potential ways to improve (Doshi-Velez & Kim, 2017; Alamri & Alharbi, 2021; Adadi & Berrada, 2018), which allows advisors to explore future scenarios and provide recommendations. The incorporation of explainable AI in learning dashboards seems to be low-hanging fruit, as visualisations and interactive visualisations in particular are already considered to be a natural way to obtain human interpretable explanations (Spinner et al., 2019).

While explanations are often put forward to increase the trust in predictive algorithms, Davis et al. (2020) state explanations should rather focus on inducing "appropriate trust" with the users. Predictive models are not 100% accurate, their accuracy can differ over the input domain, and the data underlying the predictive model can cause bias, limited applicability, etc. Therefore, users should not over trust models and be well informed about the uncertainty attached to the prediction, especially when the models are not accurate (Yin et al., 2019). In fact, as stated by Davis et al. (2020), the use of explanations can even serve debugging, selection, and validation of predictive models.

Alamri and Alharbi (2021) published a systematic literature review on research handling explainable student success prediction models. Their review showed that only two of the 15 selected papers focused on predicting student success at the program level, and that two thirds of the papers in fact relied on non-black box algorithms that are less powerful, but explainable in nature. Essa and Ayad (2012) is the most notable example of the use of explanations for success prediction models: their Student Success System (S3), using win-loss charts to show feature contribution to the prediction, was found to allow faster and more efficient detection of problem causes, and provide points of focus for actions or interventions.

While explanations are not expected to remove all barriers to the application of predictive algorithms in advising practice, explanations could be supportive in the exploration towards their inclusion. The next section shares the findings of two case studies (Scheers & De Laet, 2021; Huysmans & De Laet, 2021) that explored if and how explanations can bring prediction of student success to advising practice.

4.3.1 Two Case Studies on Explainable Advising Analytics for Advising Aspiring Students

The case studies presented in this section focus on the incorporation of a predictive model for student success in the advising of aspiring students in the first year of the Bachelor of Engineering Science at KU Leuven (see Sect. 4.3). This section is based on Scheers and De Laet (2021) and Huysmans and De Laet (2021).

The predictive model aims at predicting the academic achievement of an aspiring student, where academic achievement is encoded as the study efficiency (SE, percentage of the booked ECTS credits that a student passed)) after one semester in the bachelor program. In particular the model aims at predicting an aspiring student as "no risk" ($SE \geq 75\%$), "moderate risk" ($40 \leq SE < 75\%$), or "at risk" (drop-out or $SE < 40\%$). The input features are prior-academic achievement (math hours in secondary school, secondary school grades in math, physics & chemistry, effort level, and pressure preference) and motivation, time management, concentration, anxiety, and use of test strategies (collected using the Learning and Studying Skills Inventory of Weinstein and Palmer (2002)). As predictive black-box algorithms both Feed Forward Neural Network (Scheers & De Laet, 2021) and XGBoost (Huysmans & De Laet, 2021) showed to be applicable and resulted in an accuracy of around 75–80% and an f1-metric around 70% when predicting no risk and at-risk students. As explanations both Local Interpretable Model-Agnostic Explanations (LIME by Ribeiro et al. (2016)), LOcal Rule-based Explanations (LORE by Guidotti et al. (2018) and Guidotti et al. (2019)), a visualisation of LORE (Huysmans & De Laet, 2021), and interactive visualisation based on LIME (Scheers & De Laet, 2021) were explored. LIME and LORE are both model-agnostic local explainers. Model-agnostic indicates that the explainers generate post-hoc explanations on top of black-box algorithms. Local indicates that they provide explanations for a particular instance, in our case for a particular aspiring student. LIME is a so-called feature-importance explainer, in the presented cases it provides an explanation of an aspiring student's risk-prediction by showing to which extent each of the aspiring student' features contribute to the prediction (no risk, moderate risk, or at risk). LORE provides both a logic decision rule, showing which features are key in the prediction, and counterfactuals that indicate how the features must change to alter the classification outcome.

Figure 4.6 presents an example of a visualisation of a LORE explanation from Huysmans and De Laet (2021), Fig. 4.7 presents an example of the LIME explanation from Huysmans and De Laet (2021), and Fig. 4.8 presents the interactive visualisation built on top of LIME explanation from Scheers and De Laet (2021).

The explanations developed by Huysmans and De Laet (2021) and Scheers and De Laet (2021) were evaluated in exploratory user studies where academic advisors were asked to evaluate the use of the dashboard as a preparation for an advising dialogue or during advising dialogues. The evaluations showed that explanations help advisors to understand the black-box predictions of the risk level of aspiring students. The explanations and the interactive simulations where advisors could change the features, helped to match or contrast the advisor's mental model of student success to the prediction model, hereby also discovering the behaviour of the prediction model they believed was counter-intuitive and not consistent with their mental models.

Inconsistencies either caused advisors to challenge their mental models, to look for plausible explanations, and influenced their trust in the predictive algorithms.

		LORE			
Features:		Decision rule		counterfactual	counterfactual
Mathematics grades	>90%	X			
Physics grades	>90%				
Chemistry grades	80-90%	X		60-70%	
Hours of math	8u		>8.5		
Effort level	Average				
Affective strategies	High-medium				
Goal strategies	High	X			Low

Fig. 4.6 Example of a visualisation of LORE explanations (decision rule and counterfactuals). The LORE decision rule explains that the student is predicted as not at-risk (average grade > 8.5/20) based on prior mathematics grades >90%, prior chemistry grades between 80 and 90%, and a high level of goal strategies. The counterfactuals show that the student would have been classified as at risk if his/her prior chemistry grades would decrease to 60–70% or if the goal strategies would be low. (Figure from Huysmans and De Laet (2021))

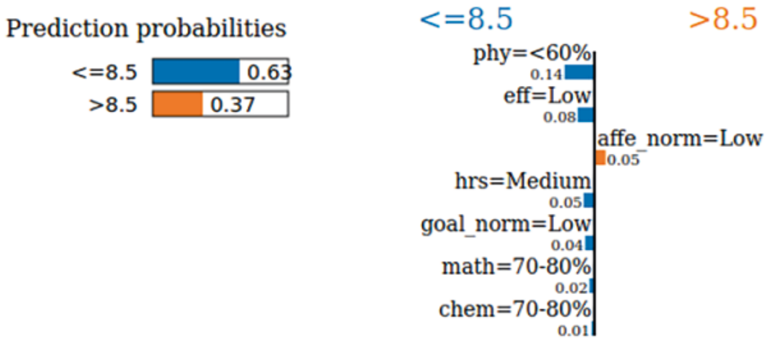

Fig. 4.7 Example of a visualisation of a LIME explanation for aspiring students' risk prediction. The visualisation shows why the student is predicted with 63% probability as at risk (average grade ≤ 8.5/20) by showing the degree to which the different features contribute to the at-risk prediction (average grade ≤ 8.5/20) or no-risk prediction (average grade > 8.5/20). (Figure from Huysmans and De Laet (2021))

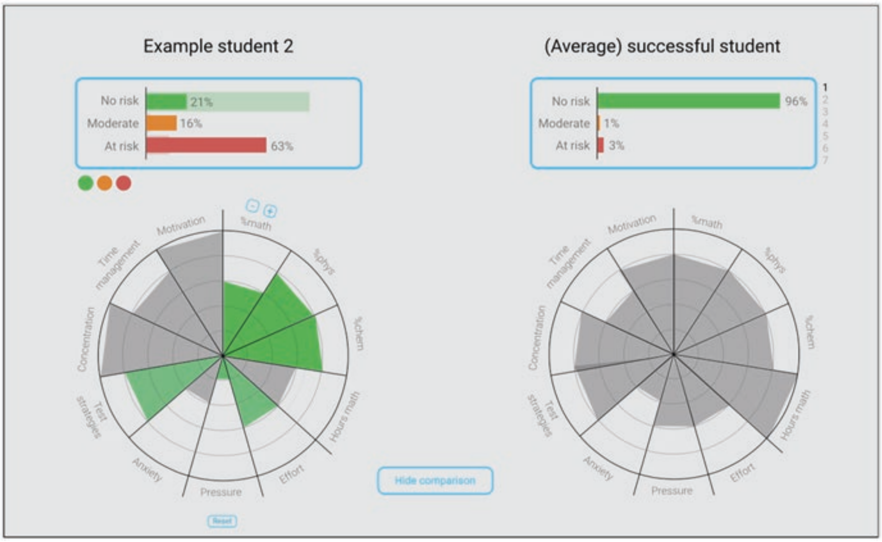

Fig. 4.8 Interactive visualisation based on LIME explanations for aspiring students' risk prediction. Below the blue prediction box with prediction probabilities, the visualisation shows the feature levels of the aspiring student. The impact of a certain feature on the prediction of a specific risk class is shown by colouring the slice that belongs to this skill into the colour of the class it contributes to, where a high colour intensity shows a larger impact. The user can interactively simulate changes of a student's features by clicking on the corresponding + and – buttons. When adapting a feature, the prediction of academic success and the impact of the (simulated) features on the risk prediction are also updated. (Figure from Scheers and De Laet (2021))

Advisors expressed concerns regarding information overload when predictions and explanations are added to advising dashboards, a common concern in dashboard design (van Leeuwen, 2015).

4.3.2 The Future of Predictive Advising Dashboards

The future of predictive advising dashboards is still uncertain. On the one hand there is a growing body of evidence that predictive elements within advising analytics receive severe criticism from academic advisors (Jones, 2019). On the other hand, there are developments within the domain of explainable AI that help to incorporate predictive algorithms to practice. The case studies from the previous section do confirm the potential of explanations to increase the usability of predictive algorithms in advising practices. Explanations by themselves will however not be sufficient to ensure the viability of predictive algorithms within academic advising. An open question is still if and how predictive advising analytics can be aligned with existing academic advising values that strongly value seeing the student as a unique individual whose context, goals and challenges will most likely never be captured within institutional data warehouses.

4.4 Conclusion

This chapter shared experiences of advising analytics in actual advising practice.

First, the chapter shared the successful experience of how the bottom-up developed advising dashboard LISSA, supporting advising dialogues between academic advisors and students, was transformed into a dashboard embedded in KU Leuven's institutional systems, processes and practices. We hope that the sharing of this successful experience will help others to identify potential ingredients for the successful deployment of advising analytics in practice. While the descriptive nature of LISSA might be 'disappointing' to institutional policymakers and administrators that see the (marketing) potential of 'real' AI and predictive algorithms, we claim that the descriptive nature of LISSA is, next to the user-centred design used, one of the key factors explaining its success. A big challenge is to marry the existing advising values, where understanding the student's individual situation, context, and goals and development of mutual trust are key, with data-supported advising practices. Descriptive dashboards developed to support the actual needs of academic advisors are an important first step towards the inclusion of data-driven techniques.

At the same time, developments within the domain of explainable AI help to bring predictive algorithms into practice. The presented case studies illustrate that research on if and how explanations can support the incorporation of predictive algorithms in advising dashboards is not futile, but at the same time is in its infancy still. More-over, we argue it is unlikely that explanations alone will pave the road for the use of predictive algorithms in actual advising practice.

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Chapter 5
Students in Focus – Moving Towards Human-Centred Learning Analytics

Carla Barreiros, Philipp Leitner, Martin Ebner, Eduardo Veas, and Stefanie Lindstaedt

5.1 Introduction

As the digitalization of education moves forward, the analysis of the digital traces of both the learning and teaching process uncovers new insights. Learning analytics (LA) is an emerging field that refers to "the measurement, collection, analysis and reporting of data about students and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long et al., 2011; Ferguson, 2012).

The project "Learning Analytics – Students in Focus" aims to use students-related data to support the teaching and, more importantly, the learning process in a higher educational context. We are an interdisciplinary team of LA and pedagogy researchers, TEL-practitioners, data scientists, and ethics and data protection experts from the Graz University of Technology (TU Graz), the University of Graz, and the University of Vienna. In this article we present the Learner's Corner which is the learning analytics dashboard at the course level developed by the TU Graz which contain three LA tools aiming at leveraging students' academic success through the promotion and development of self-regulated learning (SRL) skills (Zimmerman, 1990, 2015; Harris & Graham, 1999; Pintrich, 2000; Zimmerman & Schunk, 2001). Our research focuses on design, develop and evaluate LA tools that

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enable higher education students to make data-informed decisions about their learning process. Moreover, once proven successful, the LA tools will be integrated as LA services in the institutional Learning Management Systems (LMS) in the medium term and available to other higher education institution as open-source Moodle widgets. With this goal in mind, we generally adopted a human-centred learning analytics (HCLA) approach involving students, teachers, and other stakeholders in the iterative process of designing, developing and evaluating our LA tools. The design of effective LA tools goes beyond addressing technical and pedagogical issues. The adoption and successful use of LA analytics tools and dashboards greatly depend on usability, usefulness, and utility (Shum et al., 2019). Drawing from fields such as Human-Computer Interaction (HCI), Technology Enhanced Learning (TEL), Learning Experience Design (LXD) and Usability Engineering (UA), recent LA design approaches include the educational stakeholders in the design process to understand their needs, using a rich mix of methods and techniques. The contribution of students, teachers and other educational stakeholders is essential, but it does not come without challenges. Frequent challenges which may deter the generation of ideas and/or suggestions are lack of knowledge and/or expertise, lack of confidence, time constraints, unbalanced power relation between stakeholders, and ethical and privacy concerns (Dollinger et al., 2019). Various tools and techniques can be used to involve students and other stakeholders in the design process of LA (Prieto-Alvarez et al., 2018) – referred to as human-centred learning analytics (HCLA).

This article (i) describes the design iterations, development and evaluation process of three LA tools for students, i.e., the planner, the activity, and the learning diary; (ii) presents key results from several empirical studies used to evaluate the tools, with implications on the design of the tools; (iii) provides our insights regarding the HCLA approach benefits and limitations in practice.

5.2 Background Work

Learning analytics is, at its core, an interdisciplinary field of research and practice that brings together many disciplines to use educational data to address relevant questions for learning, teaching, and education (Siemens & Gašević, 2012). Gašević et al. (2017) propose a model of LA that refers to the following key characteristics, i.e., a field of research and practice, holistic in nature, and interdisciplinary. This model comprises three interconnected dimensions – theory, design, and data science. These dimensions group the foundational principles of LA, and only when these principles are addressed one can achieve effective results and the highest validity in both LA research and practice. The theory dimension is crucial for selecting the research questions and the hypothesis tested. Also, the theory dimension allows to produce theory grounded actionable insights for practitioners. The design dimension refers to the interaction and visualization design (allow users to interact and gain insights about learning), learning design (aims at promoting effective learning experience), and study design (research studies and evaluation in practice). The data science dimension refers to the methods and techniques to collect, measure, analyse and report data. Dimitriadis et al. (2021) consider that the design dimension has not yet been explored as deeply as the theory and the data science dimensions, referring to the need to further consolidate the three and to define principles that govern the process of designing LA tools that can be adopted in practice. To evaluate the success or failure of LA tools, one needs to consider different aspects, including the technical criteria and the adoption and effectiveness of the tools. The true challenge lies in the adoption of the LA tools by the educational stakeholders, as the "perfect" LA tool can remain unused. Therefore, embedding LA technology in schools, higher education institutions, and workplaces can be seen as a human challenge. Shum et al. (2019) demand a human-centred perspective in LA to overcome such obstacles.

The human-centredness of a system can be achieved at different levels, e.g., the design of the user interface, the evaluation of the system impact on practices, and the analysis of the shifts in the user's power and control (Fitzpatrick, 2018). Over the last decades, researchers in the field of Human-Computer Interface (HCI) have investigated and developed approaches, methodologies, and techniques that can be used to support the development of HCLA. For example, the user-centred design approach (i.e., the user as subject) is used to design and develop applications considering the users' needs. It is an iterative process that includes the analysis, design, evaluation, and implementation phases. Another example is the participatory design research (i.e., the user as a partner), where the users actively participate in the design phase (co-design) (Sanders & Stappers, 2008). The involvement of all stakeholders in the HCLA process is vital to make sure their needs are addressed. Examples of methods and techniques in the context of HCLA are (i) persona profile: help for example in the identification and characterization of the students' target group of the LA tool or identify teaching profiles; (ii) learner journeys: may contribute to understanding the context where the LA tool will be used and what are the tasks involved, leading to a better understanding of the desired features; (iii) focus group and interviews: allow to gather details through open-ended questions; (iv) sketching and prototyping are helpful for example to address concrete design problems, as it stimulates creativity and allows to express complex ideas. Through HCLA one can expect to improve both usability and usefulness of the LA tools.

5.2.1 Human-Centered Learning Analytics

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5.2.2 Self-Regulated Learning: Learning How to Learn

Accordingly, with Zimmerman (2015), SRL refers to how students become masters of their learning process. It refers to one's ability to understand and control one's learning. SRL includes setting goals for learning, concentrating on instruction, using effective strategies to organize ideas, using resources effectively, monitoring performance, managing time effectively, and holding positive beliefs about one's capabilities (Zimmerman, 2000; Schunk & Ertmer, 2000). While definitions of SRL vary to some extent, they agree on enhancing learning through proactive processes and self-beliefs.

Beyond supporting students to achieve academic success and excellence, higher education institutions aim at creating lifelong learners able to keep up with the challenges of leading a successful career and live in the twenty-first-century society driven by information and technology. In higher education learning and work-related learning, the individual must learn independently and handle diverse demands. SRL and information literacy are keystones of lifelong learning (Serap Kurbanoglu, 2003). Therefore, it is vital to support students to acquire, retain and retrieve new knowledge on their own, as well as assume responsibility for their learning (Shum et al., 2019).

Several SRL models include aspects of metacognition and self-regulation. Panadero (2017) analyses and compares well-known models for SRL, presenting a repertoire that educators and researchers can use to select the appropriate model for their interventions. Our research focuses on Zimmerman's cyclical model of SRL (Zimmerman, 2002, 2008), which consists of three phases: forethought, performance, and self-reflection. Firstly, in the forethought phase, the students analyze the task, define goals, and formulate strategic plans to reach them, considering their self-motivation beliefs. Secondly, in the performance phase, the students execute the learning task involving processes of self-control (e.g., self-instruction, attention focusing) and self-observation (e.g., metacognitive monitoring, self-recording). Lastly, in the self-reflection phase, the students evaluate their performance, which generates self-reactions. This SRL model considers the different stages of a learning cycle, which allows us to investigate LA visual tools, that promote and support SRL practices across the three phases. These LA visual tools are often presented as a learning dashboard.

5.2.3 Learning Dashboards: Perceiving Learning At-a-Glance

The visualisation task is one of communication, which intends to effectively communicate the information contained in datasets using graphical means (Laidlaw et al., 2005). In fact, visualization builds on semiotics (Bertin, 2010), and visual perception (Carpendale, 2003; Healey, 2001; Mackinlay, 1986) to develop visual encoding principles (Munzner, 2011; Ware, 2012) that encourage visual thinking. In constructing a visualization, it is important to consider what kind of data should be represented and how best to encode it in graphical structures to foster analytical operations. Visualization aims to elicit understanding and insight (McCormick, 1988), relying on the innate perceptual abilities of people to detect patterns, differences, connections or similarities in graphical representations (Shneiderman, 1996). A dashboard is defined as "… a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance" (Few, 2006). Dashboards are used in many contexts and for various purposes, and their design is also very diverse (Sarikaya et al., 2019). Therefore, dashboards share the goals regarding visual encoding but strive for a compact representation of essential aspects that can be picked up at a glance. In our research, we are interested in the use of dashboards in education, which are often referred to as learning dashboards, educational dashboards, and LA dashboards. A LA dashboard can be defined as "a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" (Schwendimann et al., 2017). In higher education environments LA dashboards are increasingly being adopted by students, faculty, and university administrators to support decision making. Clearly, different stakeholders have distinct goals, and the learning dashboards must be designed to address their needs while curating for issues such as privacy, justice, equity, diversity, and inclusion (Williamson and Kizilcec, 2022). Jivet et al. (2020) propose a set of design recommendations for learning analytics dashboards, which include the strategic involvement of students in the design process to increase adoption, promote transparency, recognize and cater to students with different SRL levels. For example, students' LA dashboards typically present data about the student academic progress, e.g., course performance and behaviour (Leitner et al., 2021), as well as LA tools to support SRL, e.g., reflect, time management (Pérez-Álvarez et al., 2017). Faculty's learning dashboards allow teachers for example to monitor students' performance and obtain feedback about the teaching process, and the university staff's dashboards focus on manage and support students and teachers.

5.3 Learner Corner: Co-designing a Learning Analytics Dashboard to Support Self-Regulated Learning

The Learner's Corner is the learning analytics dashboard at the course level developed by TU Graz in the context of the "Learning Analytics – Students in Focus" project. The Learner's Corner dashboard is integrated into the learning management system of our institution (based on the open-source learning platform Moodle, https://moodle.org). The dashboard is accessible through the left sidebar menu in the courses where the LMS administrators activate it. The Learner's Corner dashboard comprises tools to support students in regulating their learning process. Self-regulated students are proven to be effective learners that can set goals, plan, monitor their progress, reflect, and define strategies for the future (Zimmerman, 1990, 2015;

Harris & Graham, 1999; Pintrich, 2000; Zimmerman & Schunk, 2001). Currently, the Learner's Corner dashboard includes a planner tool, an activity tool, and a learning diary tool, which aim to contribute to the understanding and improvement of the students' ability to self-regulate their learning process. Even though our project focuses on the students' needs and the students' view of the dashboard, we also investigate the teachers' view to facilitate and support the teaching process and monitor the students' learning process.

As mentioned, we followed a HCLA approach, bringing to the forefront the needs of the users and the will to partner with the users in the co-creation process to design the Learner's Corner dashboard. This approach is an iterative process and typically consists of four steps, the analysis, the design, the prototype implementation, and finally, the prototype evaluation. We started by performing an extensive literature review on related topics such as human-centred design, participatory design research, human-centred learning analytics, SRL, information visualization, dashboards, learning analytics dashboards, data literacy, ethics and legal issues within the context of LA. Grounded on the theoretical foundation and the analysis of available LA tools, we began the design, implementation and evaluation of the different LA tools described in this section.

5.3.1 Analysis: Identification of the Stakeholders and Use Case Definition

We started by identifying the key stakeholders of our project, describing their needs and the context in which they may use the Learner's Corner dashboard. Within the project context, we identified the following main stakeholders: the students, the teacher and teaching staff, e.g., tutors, the dean of studies, the university, and the researchers. We focused on the students and their needs. However, we thought it important to consider the needs of teachers and the teaching staff, as they are responsible for the didactical and organizational integration of the LA dashboard at the course level. Our next step was the definition of students' personas and the description of several scenarios that describe when and with what intent the students may use the LA dashboard to acquire or develop self-regulated skills and how they might act to achieve a goal using the dashboard. The personas and the scenarios were discussed with our experts and later with the educational stakeholders to identify the users' needs and possible constraints. We then decided to proceed with three scenarios that correspond to the current LA tools integrated into our dashboard, i.e., the planner tool, the activity tool, and the learning diary tool. Next, we defined the concrete use cases that describe in further detail the goals of the system (higher level requirements were elicited). The use cases were validated by the didactic, the LA, the ethical and privacy, and the technical team experts. This step is, in our opinion, crucial, as we not only address the needs of the students but also validate them on a pedagogical level and guarantee the trustworthiness and legal compliance of the final tools.

5.3.2 Designing the Learner's Corner Dashboard Tools

Our next step was to produce design solutions for each of the three use cases. We started the ideation process, where the team experts generated several ideas on how each of the LA tools should look and behave. These broad ideas were realized in low fidelity paper prototypes (see Fig. 5.1) used in a co-design workshop with nine students. The personas, the scenarios, and the initial paper prototypes were used to generate new design ideas and further develop some of the already existing concepts. Next, given the co-design workshop results and insights gained, we created a high-fidelity clickable prototype using a prototyping tool. Also, we presented and discussed the Learner's Corner dashboard prototype with the participants of a workshop on the topic of time management promoted in collaboration with our university. About 120 students participated in the online workshop, where we collected feedback and ideas using a collaborative board and a questionnaire. Finally, we updated the prototype mock-ups and the use case description accordingly.

5.3.3 Prototype Implementation and Evaluation

Our front-end designer and technical developers implemented three versions of the Learner's Corner dashboard, which is integrated into the learning management system of our institution. Each version of the dashboard was then evaluated using a multi-method approach, where both qualitative and quantitative data were collected

Fig. 5.1 Examples of initial low fidelity paper prototypes created to discuss ideas about the Learner's Corner dashboard tools

and analysed. These studies mainly targeted the students but also included interviews with teachers and teaching staff as they are responsible to configure some of the Learner's Corner tools, e.g., in the planner tool teacher and teaching staff should add the course milestones and set feedback defaults. The Learner's Corner dashboard was activated in courses explicitly selected based on the course design and the size of the cohort. In the first course class, the researchers presented the Learner's Corner dashboard and provided online access to further information about the study. Also, the researchers asked the students to participate in the corresponding study voluntarily. The experimental procedure was described to the students as follows; (1) fill out the self-regulated skills questionnaire, (2) use the tools during the semester, (3) provide feedback about the tools using the email and/or the study forum, (4) participate in the calls for interviews and workshops, (5) fill out the final questionnaire at the end of the semester. The results of the conducted studies in each iteration lead to the next improved version of the LA dashboard, as we aim to improve the Learner's Corner dashboard continuously. Figure 5.2 depicts the Learner's Corner dashboard design, implementation, and evaluation process, which comprises three iterations corresponding to an academic semester since the start of our project. Figure 5.3 details the conducted studies, e.g., the number of participants and instruments used.

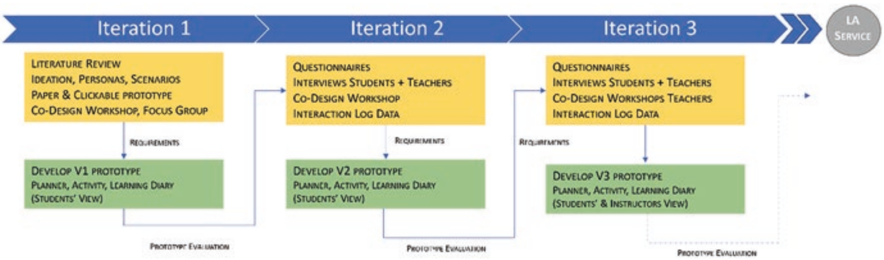

Fig. 5.2 Learner's Corner dashboard design, implementation and evaluation process

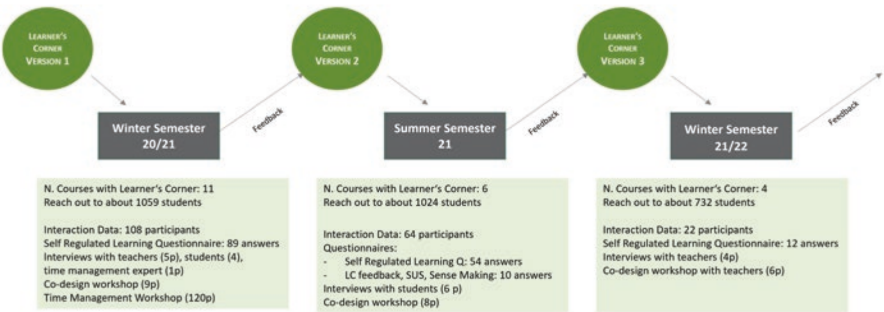

Fig. 5.3 Learner's Corner dashboard evaluations overview

5.3.4 *Learner's Corner Learning Analytics Dashboard Prototype*

The Learner's Corner learning analytics dashboard is a prototype composed of three visual tools that aim to support students in acquiring or developing SRL skills such as setting goals, planning, managing time, monitoring performance, comparing performance with peers, and reflecting. The three tools included in the students' view are the planner, the activity, and the learning diary. The tools are being designed and evaluated with the experts that compose the project team, the students, the teachers, and other educational stakeholders, e.g., the students' union, the technical team supporting teachers using educational technology in our institution. Figure 5.4 depicts an overview of the Learner's Corner dashboard current version as per the students' view.

The *Planner* tool's primary goal is to provide an overview of the course milestones set by the teacher and the personal milestones set by the student. The planer is, at its core, a planning tool and a time management tool. The course's milestones are placed in a timeline, which allows the students to monitor their progress at one glance. All milestones are characterized by a title, a date/time, and a completion status (completed, not completed), among other properties. Also, milestones can be added, edited, and deleted. The teachers are responsible for creating course milestones according to the course design and didactical approach. For example, in a flip-classroom course, the teacher can create a milestone for each class, informing students about the content that should be covered to prepare the class attendance, a milestone for a quiz, a practical exercise or an exam. Teachers can also set automatic reminders for students to complete the milestone's work within the time frame. These reminders are delivered by email, LMS notification system, or both. Similarly,

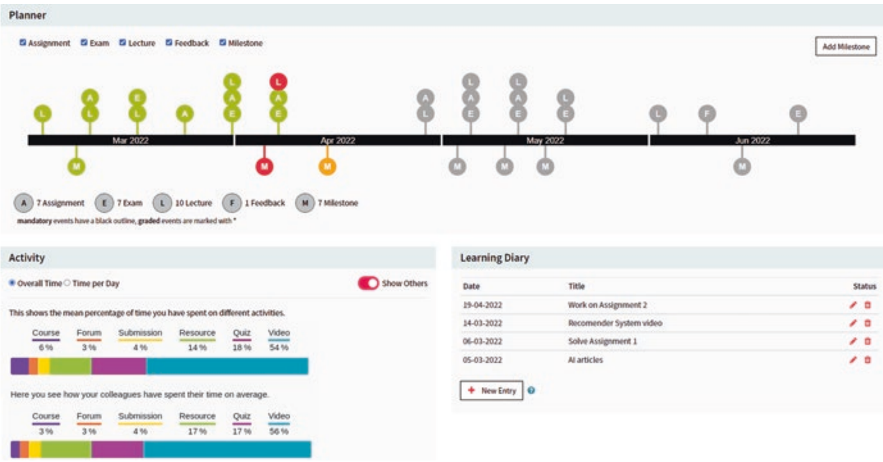

Fig. 5.4 Learner's Corner dashboard comprises three tools: the Planner (top), the Activity tool (bottom left), and the Learning Diary tool (bottom right)

students can create their personal milestones and set their preferences regarding the reminders. Most importantly, students should keep track of the completion status of each milestone during the semester. A traffic light visual encoding is used to represent the completion status, i.e., a milestone is presented in green colour if the student sets the completion status as completed; a milestone is shown in yellow colour if the deadline is approaching, and the milestone's status is "not completed"; if the deadline is overdue a milestone is presented in red colour, otherwise the milestone is shown in grey colour. In addition, it is possible to identify the graded milestones (part of the grade) and the compulsory milestones. Students can filter the information presented in the planner, zoom in/out the timeline, consult the legend, and see the milestones summary when hovering the mouse (i.e., date, title, number of students that completed the milestone). Also, the system sends a monthly report to the students that summarizes their progress. Figure 5.5 depicts an example of the planner tool, where one can see the milestones set by the teacher (top) and the personal milestones (bottom).

The Activity tool aims at reporting the students' main activities for the course and the time spent in each of these activities, which allows students to monitor and perhaps reflect on their learning. The tool offers two visual graphs showing the students' online activity in the institutional learning management system and other institutional platforms, e.g., navigation, interaction with course resources, video streaming, and forums. Figure 5.6 depicts the two visual representations that students can select from, a stacked bar chart (left) and a line chart (right). Students can also decide to compare their data with their peers by enabling the data visualization about other students. Teachers can monitor the aggregated information about all the students' activities.

Learning diaries are a self-explorative, didactical practice to reflect upon one's own's learning process. Therefore, the *Learning Diary* tool's primary goal is to

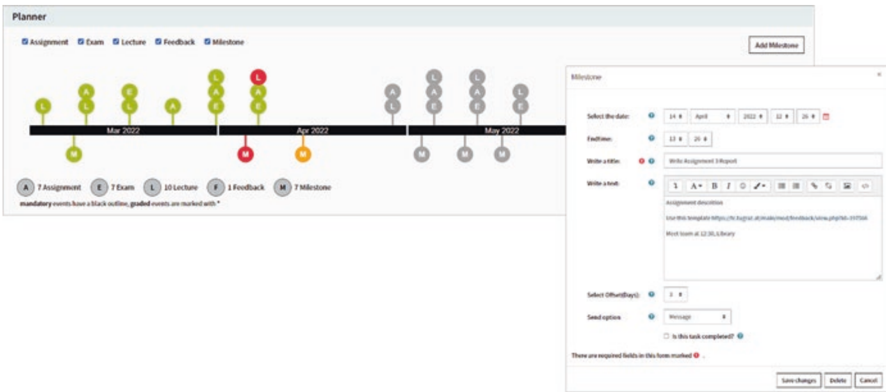

Fig. 5.5 Learner's Corner dashboard- Planner tool example of a course timeline (left). The course's milestones set by the teacher are presented at the top of the timeline, while the student's personal milestones are presented at the bottom. The different colours inform the completion status of the milestones. The student fills the milestone form (right) when adding a new milestone

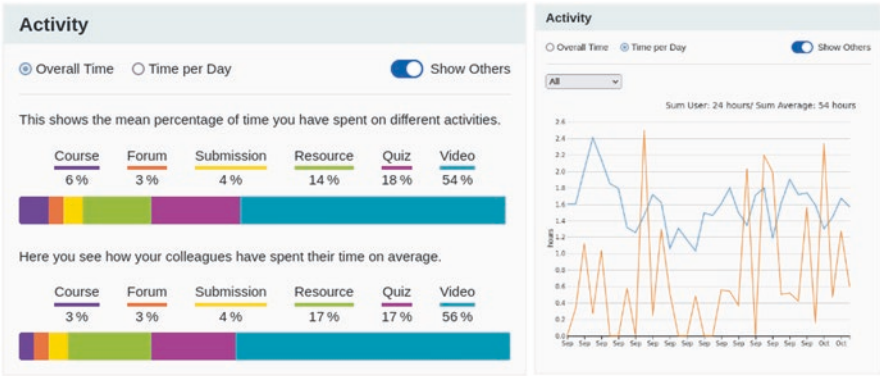

Fig. 5.6 Learner's Corner dashboard – Examples of the two visualizations of the Activity tool. The first shows a stacked bar chart with the student's online activities for the course and time distribution (left). The second shows a two-line chart with the time spent per day (right)

function as an instrument of reflection and enhance awareness of one's behaviour, enabling the individual to change his/her learning habits. This tool can provide insights to both students and teachers. Our Learning Diary tool allows students to add, edit, and delete diary entries. Each diary entry may collect large amounts of data, e.g., details about a learning event, materials, thoughts and feelings, insights and action plans. However, students are free to answer at their will as most fields are not mandatory. Each diary entry comprises five sections that describe the learning event while encouraging students to reflect while answering triggering questions. The first section is called General and collects the basic information about the learning event, i.e., the title, the date, start and end time, and the goals of the learning event. The second section is called the Planner as it allows the student to associate a learning diary event with a milestone in the planner tool or a course resource. The third section is called Activity and collects information about what the student did during the learning event. It presents several options that the student can select from, e.g., read, take notes, organized, and allows the student to add other activities. The fourth section is called Materials and collects information about which materials the student used during the learning event, e.g. course slides, course script, videos. Students can also add references to extra materials and resources, e.g., a link to an online article on the topic. Lastly, the fifth section is called Self-reflection and is composed of a set of questions, such as "what did I learn?", "What was new for me?" "What did I not understand? Why?", "Did I achieve my goals for the learning event? Why?", "What would I do differently next time?". Figure 5.7 depicts the learning diary tool in the students' view. On the left-hand side, we can observe the Learning Diary tool and an example of a diary entry on the right-hand side. Teachers can only see aggregated information about the tool's usage, such as the average number of diary entries per student.

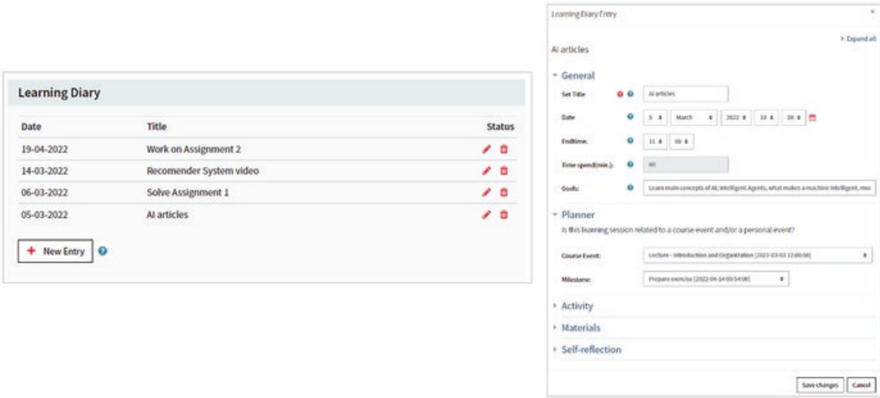

Fig. 5.7 Learner's Corner dashboard – Learning diary tool example depicting the list and management of diary entries (left). A diary entry is composed of five sections (right)

5.3.5 Key Findings with Design Implications

This section summarises the key findings of our empirical studies on the Learner's Corner dashboard, considering the students' feedback collected through the questionnaires, the workshops, the email and forum messages, and the conducted interviews described in previous Sect. 5.3.3.

The planner tool is the students' favourite tool on the Learner's Corner dashboard. Students liked the overview of the milestones of the course distributed through the semester and considered that it is easy to track where they stand and what is to come. Also, the majority of the students appreciated the email reminders of deadlines approaching and the monthly reports about their performance but refer that it is important to be able to personalize the reminders accordingly to their preferences. Some students revealed concerns regarding the number of emails they would receive from all the courses they are enrolled in, which may be overwhelming and cumbersome. Another commonly suggested feature by the students was the creation of a view that merges the milestones of all courses, as this would allow better planning. To address this feedback, the current version of the dashboard already enables the personalization of the reminders, allowing students to change the setting for each milestone. Also, the reminders can now be received via email or the notifications of the learning management system of our institution. Currently, we are investigating how to integrate information about more than one course in the planner view.

Students find the activity tool interesting and useful to monitor how long and how they spend their time in a course. However, several students were concerned with the accuracy of the estimated time for the online activities. Also, the time spent in offline learning activities should be considered to reflect the actual effort. Also, the majority of the students think that this information should be shared with the teachers. Some students said to have mixed feelings regarding the possibility of comparing their data with their peers, as they refer to feeling stress and pressure to perform as well as their peers. Considering the students' feedback, we included in the current version of the dashboard the possibility to show or hide the peers' data. We decided to use the information collected in the Learning Diary tool to address the issue of collecting information about the time spent learning offline in an accurate manner. However, we are still to incorporate this information in the Activity tool.

The Learning Diary tool was appropriated in different ways by the students. Some students use it as an organizational tool that allows them to make plans, set goals, take notes, and organize files. Other students used it as a reflection tool, and other students saw it as a way to provide quick feedback to the teachers, e.g., regarding materials, the complexity of the topics, doubts. Overall, students liked the tool and offered many suggestions and ideas on how to improve it, e.g., students suggested connecting the learning diary entries with the milestones of the planner tool; students suggested splitting the learning diary into different sections; students indicated that filling out the fields in the diary entry should be optional; students suggested to offer predefined answers to some of the questions allowing them to select the ones that apply, with the possibility of adding new ones. These and other suggestions are already implemented in the latest version of the dashboard. However, the Learning Diary tool raised ethical and privacy concerns, which the students considered can be surpassed with total transparency about who has access to the data and with what purpose.

5.4 Discussion

While the LA field of research has been evolving in the last decade, human-centred learning analytics is relatively new. Human-centred learning analytics refers to the adoption and adaptation of design practices already established in the HCI research field to engage with educational stakeholders during the design process (Shum et al., 2019). The human-centred design approaches are relevant in the context of LA to create tools that support students, teachers, and other educational stakeholders effectively (Dimitriadis et al., 2021). Teachers are typically the educational stakeholders that have been more involved in LA co-design studies. However, LA design projects that engage with other stakeholders emerged in recent years (Shum et al., 2019). Our project focuses on the students, and therefore it was crucial to involve students in the design of the Learner's Corner dashboard. Next, we reflect on the benefits and challenges felt during this process, pointing out strategies that, in our opinion, allowed us to overcome some of the challenges and limitations.

There are several advantages associated with the Human-centred design approach, which in our experience, transfer to the LA context. First, this approach is often associated with the improvement of the usefulness and usability of the system, and it enhances "effectiveness and efficiency, improves human well-being, user satisfaction, accessibility and sustainability; and counteracts possible adverse effects of use on human health, safety and performance" (ISO: Ergonomics of human-system interaction—Part 210 ISO 9241-210:2019). Indeed, partnering with students, teachers and other educational stakeholders allowed us to understand the students' needs better, find solutions that address these needs and create a solid basis for developing the prototype, decreasing the barriers to adoption of the dashboard. However, we identified several challenges related to adopting the human-centred design approach. First, we verified that the students willing to participate in our initiatives are typically effective learners who already have developed self-regulated skills and are looking for tools to support their practices. On the one hand, these students bring their rich experiences as effective learners to the table. Still, on the other hand, we think that it is necessary to engage with students that do not reveal self-regulated skills as they are the ones that would benefit the most from using our dashboard. Second, the number of students willing to participate in the studies is significantly low. However, we need to mention that our project, until now, has been running during the CoVid-19 pandemic, which presents several challenges (Ebner et al., 2020), e.g., conditioned access to the students and required that all contacts occur online. Thirdly, students are not the experts in pedagogy or designers and therefore is essential to include teachers and other educational stakeholders in the design process. Fourthly, we recognize that this approach is time-consuming and requires more effort. Lastly, this approach requires an interdisciplinary team, which may be hard to achieve in smaller projects.

One of our projects' goals is to disseminate and transfer the developed ideas and prototypes from the research environment to the practical application. Technology transfer is a complex process, and quality research results are insufficient to ensure a successful process. Even when LA tools are available, this does not necessarily translate into the adoption of the new technology. Several factors can potentially influence the adoption of LA technology, e.g., perception of usefulness, familiarity with technology, respect for ethical values and privacy requirements. To increase the adoption of LA technology in our institution, it is necessary to develop a common knowledge among all the educational stakeholders about the technology's benefits and limitations and clarify any ethical and privacy concerns related to the technology building trust. The establishment of an active LA community in our institution is crucial. We consider that embracing the Human-centred learning analytics approach is an important step in creating strong trust-grounded interactions with LA technology.

Moreover, we consider that higher education institutions should offer LA technology as a service that students can decide to use or not. Also, students should control their data instead of assuming the role of data subjects (Gosch et al., 2021). This paradigm shift empowers students and amplifies students' responsibility to use LA services and manage their data. Even though we validated our use cases concerning ethical and privacy issues, we are still investigating the design and technical implications, as well as the challenges associated with the technology transfer in the long term.

5.5 Conclusions and Future Steps

We adopted the HCLA approach to create our LA dashboard and identified the following key benefits: (i) active involvement of the educational stakeholders is crucial to understanding their needs and the context in which the LA system will be used, (ii) the iterative process allows to progressively improve the design solutions using the users' feedback, (iii) an interdisciplinary team is essential to collect insights and expertise from the different fields collaboratively; (iv) HCLA serves as a promotor of LA trustworthiness, and (v) HCLA can be seen as a first step to establish an active LA community and overcome several challenges in establishing and implementing LA in higher education institutions (Leitner et al., 2019). Given the positive experience with the Human-centred learning analytics approach, we will continue to use it to improve the Learner's Corner dashboard, enriching it with new tools for students and teachers. Currently, we are defining a new use case for a tool that exposes the grading schema of the course and allows students to monitor their progress.

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Chapter 6
LALA Canvas: A Model for Guiding Group Discussions in Early Stages of Learning Analytics Adoption

Isabel Hilliger and Mar Perez Sanagustín

6.1 Introduction

Since the field of Learning Analytics (LA) emerged in the early 2010s, a rising number of frameworks and models have been created to guide the design and implementation of LA in different educational settings. Khalil et al. (2022) defines frameworks as templates or high-level visualisations of different elements and processes that are relevant for a particular outcome (e.g., data-based transformation of teaching and learning), and models as a defined sequence of operations to realise the phenomenon in question (e.g., design and implementation of LA). As such, Khalil et al. (2022) argues that frameworks flow from a particular vision of what LA adoption might imply for a particular context, while models presume the existence of an implicit or explicit framework to decide what should be included or excluded during the development and deployment of a specific LA tool.

Considering the persisting challenges to scale up and sustain LA adoption, such as getting stakeholder buy-in or leading with ethical issues (Tsai, 2021), LA frameworks and models have become study objects for the LA field. For example, Dawson et al. (2018) acknowledge existing conceptual LA models by classifying them into three categories: input models, output models, and process models (see examples of the three types of models in Table 6.1). First, input models typically propose a set of elements that are previously required for LA adoption (Dawson et al., 2018). Then,

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https://doi.org/10.1007/978-3-031-27646-0_6

Table 6.1 Examples of different types of models for LA adoption according to Dawson et al. (2018)

	Model name	Model description	Reference
Input models	Maturity index	Conceptualizes the maturity required for LA adoption in terms of infrastructure, IT involvement, investment, and culture	Bichsel (2012)
	Learning analytics readiness index (LARI)	Identifies infrastructure, culture, data, and processes as key factors for LA adoption.	Arnold et al. (2014)
	Generic framework for learning analytics	Refers to data, objectives, instruments, stakeholders, and internal and external constraints as key dimensions that influence LA adoption.	Greller and Drachsler (2012)
Output models	Maturity of learning analytics deployment	Represents LA adoption as a five-stage process that goes from awareness to transformation.	(Siemens et al. (2013)
	Directions for learning analytics adoption	Presents three distinct components to guide LA adoption towards effective interventions: data, model, and transformation.	Gasevic et al. (2016)
Process models	SHEILA policy framework	An iterative process to guide the development of evidence-based policy for LA adoption through active engagement with relevant stakeholders.	Tsai et al. (2018)
	Learning analytics continuous improvement cycle	A continuous improvement cycle with three steps: data gathering, information processing, and knowledge application.	Elias (2011)
	Learning analytics reference model	A model for LA adoption based on four questions: What kind of data does the system gather, manage, and use? Who is targeted by the analysis? Why and how does the system perform the analysis of the collected data?	Chatti et al. (2012)

output models represent outcomes expected from the process of LA adoption according to different levels of organizational readiness and maturity (Colvin et al., 2017; Dawson et al., 2018). Finally, process models portray LA adoption as an iterative process that requires the systematic engagement of different stakeholders (Dawson et al., 2018). In these lines, Zhao et al. (2021) highlights specific LA frameworks such as the ones proposed by Elias (2011) and Chatti et al. (2012).

Khalil et al. (2022) expanded the previous analysis by conducting a systematic review of LA frameworks proposed between 2011 and 2021. As a result, 46 frameworks were analysed using a code scheme agreed upon by three researchers, aiming to provide insights concerning the value systems embedded within existing templates or models. Out of all the frameworks analysed, 28 frameworks were either partly or fully based on empirical research. The combination of conceptual and empirical research not only grounds frameworks in institutional realities, but also enables the emergence of new dimensions to illustrate the implications of LA adoption in a more holistic way (Khalil et al., 2022).

However, the incorporation of empirical data does not necessarily make frameworks or models transferable or scalable to other contexts. This seems particularly important considering differences among regions regarding their educational contexts and their use of learning technologies and educational data. Inclusive literature reviews have been conducted to analyse research productivity in different territories, including articles written in Spanish, Portuguese, and other languages, showing that there is a disproportionate number of studies documenting the design and implementation of analytical tools in developed contexts compared to developing regions (Cechinel et al., 2020; Suthers & Verbert, 2013). An uneven participation in the field leads to gaps in knowledge, disregarding the existence of a wide variety of needs and local nuances that could affect the adoption of analytical solutions (Cechinel et al., 2020), such as the availability of data infrastructure, LA experts, or data protection regulations. Although some researchers have tried to fill this gap by identifying needs in developing regions (Hilliger et al., 2020a), further studies should analyse frameworks and models to guide the design and implementation of LA tools to meet those needs in developing educational settings.

Considering the need for more studies to analyse LA adoption in a specific context (Khalil et al., 2022; Tsai et al., 2019), this chapter presents the LALA Canvas: a conceptual model to guide group discussions at universities where LA adoption is still at an early stage. The LALA Canvas builds upon the findings of the SHEILA project (i.e., Supporting Higher Education to Integrate Learning Analytics). As it is presented in Table 6.1, the SHEILA project proposed a framework that consists of an iterative process based on the ROMA model: an existing guide for developing evidence-based policy through active engagement with relevant stakeholders (Young & Mendízabal, 2009; Young et al., 2014). Khalil et al. (2022) suggest using the SHEILA framework as a starting point due its successful usage in a wide range of context. However, the maturity levels of LA adoption in developing regions such as Latin America fall far behind European levels because the LA concept is not widely known and LA initiatives are still scarce or implemented on a small scale (Cechinel et al., 2020; Lemos dos Santos et al., 2017). Thus, the LALA Canvas components are based in ROMA as in the SHEILA project, but in different order and depth to consider the growing maturity of LA in specific university settings.

6.2 LALA Canvas as a Rapid Model for LA Adoption in Latin American Universities

The LALA Canvas was created in the context of a project entitled ‘Building Capacity to Use Learning Analytics to Improve Higher Education in Latin America’ (hereinafter referred to as LALA project). This project was financed by the Erasmus + program of the European Commission, and its objective was to build local capacity to design and implement LA tools in Latin American universities. To meet the project objective, European universities had to collaborate with Latin American institutions to propose guidelines and solutions to facilitate the adoption of LA. Specifically, this project involved three European partners: Universidad Carlos III de Madrid

(UC3M), University of Edinburgh (UEdin) and KU Leuven (KUL); along with two partners from Chile: Pontificia Universidad Católica de Chile (PUC) and Universidad Austral de Chile (UACh); and two partners from Ecuador: Universidad de Cuenca (UCuenca) and Escuela Superior Politécnica del Littorals (ESPOL).

Since the LALA project started, partners generated different types of outcomes (Muñoz-Merino et al., 2020), including the development of a set of guidelines to design, implement, adapt, and adopt learning analytics tools at an institutional level. This set of guidelines is known as the LALA framework (Pérez-Sanagustín et al., 2018), and it organizes different methodologies and instruments in four manuals. Considering prior research about LA adoption, each manual addresses a dimension that has proven to be relevant for scaling LA initiatives, including:

1. An institutional dimension related to the political and strategic aspects of the institution.
2. A technological dimension related to the technical aspects associated with the design and implementation of technological tools.
3. An ethical dimension related to the ethical aspects of data treatment and management.
4. A community dimension related to the generation of a research community and good practices regarding learning analytics in Latin America.

Within the institutional dimension, project partners considered a series of activities to assess the current and the desired state of an institution with respect to LA adoption, as well as the policies and strategies established for the management of educational data. Taking as a reference the European SHEILA project, LALA project partners designed materials to guide the development of activities based on the ROMA (Rapid Outcome Mapping Approach) framework (Young et al., 2014). One of these materials was the LALA Canvas model, which consists of a template used to guide a group discussion about the current state of a higher education institution in terms of LA adoption. This model has six components adapted from the ROMA framework (Fig. 6.1):

1. *Political context:* Refers to external/internal policies or regulations that currently affect change management within an institution. In the context of LA adoption, there may be regulations that affect the management of educational data (external legal structure), or processes for evaluating academic or teaching performance (internal policies).
2. *Influential actors:* Refers to the identification of individuals or groups of people who currently intervene directly and indirectly in the management of an institution. In the context of LA adoption, these actors are the ones who intervene in data-based strategies, either as beneficiaries or managers
3. *Desired behaviours:* Refers to expected results of an intervention, describing behaviours that require improvement. In the context of LA adoption, the expected results could be improved student learning, changes in teaching practices or institutional decision-making

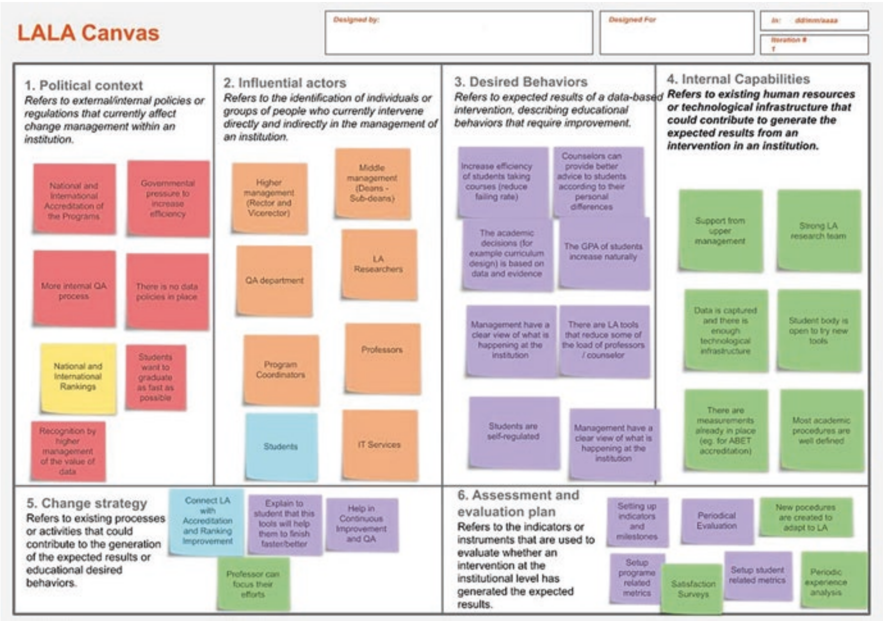

Fig. 6.1 Example of LALA Canvas model used in the context of the LALA project

4. *Change strategy:* Refers to existing processes or activities that could contribute to the generation of the expected results or desired behaviours. In the context of LA adoption, these activities could involve existing data-based initiatives, as well as efforts for generating new internal abilities.
5. *Internal capabilities:* Refers to existing human resources or technological infrastructure that could contribute to generate the expected results from an intervention in an institution. In the context of LA adoption, this dimension could represent existing technological tools or the availability of skilled professionals and researchers for data analysis and visualization.
6. *Assessment and evaluation plan:* Refers to the indicators or instruments that are used to evaluate whether an intervention at the institutional level has generated the expected results. In the context of LA adoption, these indicators could be metrics obtained from the use of educational data in the instances established by the institution.

The LALA Canvas model was designed to be completed during group discussions as part of a participatory process. This participatory process consists of a set of steps to ensure that the discussion helps identifying potential needs for LA strategies in a university where LA initiatives are still scarce or implemented on a small scale. It is recommended to engage at least three people from the same institution (or from similar educational settings), but with different institutional roles (e.g., faculty, program chair, information technology leaders, among others). The discussion about each one of the components should be orchestrated by a facilitator throughout a one-hour workshop (approximately). The steps are the following:

(a) The facilitator (e.g., an LA expert or someone in the institution familiar with LA) introduces the concept of LA and the objective of the LALA Canvas and briefly presents each one of its components.
(b) Each participant in the workshop lists elements within each one of the LALA Canvas components. It is advisable to offer a limited time to complete each dimension (e.g., 5 minutes). Ideally, the canvas can be printed in a large format, so participants can add ideas in each component using *post-its* (see Fig. 6.2).
(c) Finally, the facilitator invites participants to present the elements listed within each component, and then discuss about the main conclusions. If there is more than one group, each group can summarize their conclusions to reach a consensus.

After applying the LALA Canvas, it is expected that higher education stakeholders became able to analyse the current status of their institution in terms of LA adoption. Specifically, they can identify desired behaviours and internal capabilities to design and implement LA tools at an institutional level.

To evaluate the use and deployment of the LALA Canvas, we followed a design-based research approach throughout the LALA project. Barab (2014) defines design-based research as a series of interventions in which different research methods are used to derive a theory or a tool in a real-world setting. In the context of this project, we conducted a series of workshops to capture lessons learned about the

Fig. 6.2 Use of LALA Canvas template in a face-to-face workshop Deployment and evaluation of the LALA Canvas: methodological approach

framework and improve it. In some cases, the LALA Canvas also served as a rapid way to assess the needs for LA tools, so workshop participants could design mocks up of LA tools (see Fig. 6.3).

Between 2018 and 2021, the LALA Canvas was used by 371 HE stakeholders during four workshops conducted at universities from different Latin American countries, including Chile, Brazil, Costa Rica, and Perú. Table 6.2 describes the number of attendees per workshop, the purpose of the survey applied at the end of each workshop, and the number of responses obtained from workshop participants.

6.2.1 Workshop Participants, Data Collection and Analysis

Workshop Held on March 21st, 2018, in Santiago, Chile

This workshop had 29 participants from higher education institutions in Chile, which differ in administration (private versus public), location (metropolitan versus regional), and size (in terms of enrolment). During this workshop, LALA project researchers applied the LALA Canvas, so further group discussions could be held about the potential use of LA tools in their institutions. Out of the 29 workshop participants, 17 voluntarily answered a paper survey to assess the perceived benefits of using the LALA Canvas and evaluating the importance of its components. Participants could choose answer options within a 5-point scale, with 1 being "not beneficial" and 5 being "extremely beneficial". These answers were descriptively

Fig. 6.3 Mock-up of LA dashboard that was design based on elements listed on the LALA Canvas

Table 6.2 Workshops in which the LALA Canvas was used to guide group discussions about LA adoption in different Latin American universities

Workshop title	Location	Date	Number of attendees	Number of survey participants	Survey objective
Learning analytics for quality management in higher education	Santiago, Chile	March 21st, 2018	29	17	Assess perceived benefits of using the LALA Canvas and evaluating the importance of its components.
Student success informed by learning analytics and artificial intelligence	Lorena, Sao Paulo, Brazil	May 28th, 2019	173	122	Evaluate aspects related to the LALA Canvas workshop.
Learning analytics and artificial intelligence to improve the quality of higher education	San José, Costa Rica (online)	August 18th, 2020	154	149	Evaluate the perceived usefulness of the LALA Canvas from a qualitative perspective.
International learning analytics program	Lima, Perú (online)	August 27th, 2021	15	14	Evaluate the perceived usefulness of the LALA Canvas from a quantitative perspective.

analysed by counting the number of responses per option. Additionally, we asked participants to indicate which LALA Canvas component resulted most important for assessing needs for LA adoption, and we used the frequencies of mentions to reorganize the layout of the LALA Canvas model. Quotes were also extracted from answers to an open-ended question in which participants could make comments about the workshop.

Workshop Held on May 28th, 2019, in Lorena, Sao Paulo, Brazil
The STHEM consortium organized this workshop, which is a network of 64 public and private institutions in 14 states of Brazil and Portugal (https://www.sthembrasil.com/). This consortium is supported by Laspau, an organization affiliated with Harvard university, and whose mission is to strengthen higher education in Latin American and the Caribbean. Laspau's program of university innovation invited a LALA project researcher to lead a workshop focused on LA and artificial intelligence in higher education. With this focus on mind, the researcher presented an overview of research fields that emerged from the accumulation of educational data. This presentation was followed by an application of the LALA Canvas to inform the design of a mock-up of a potential LA tool. Out of the 173 workshop participants, 122 voluntarily answered a survey with a 7-point Likert scale to evaluate aspects related to the LALA Canvas workshop. Answers to each 7-point item were averaged to quantify the level of agreement of participants with different aspects related to workshop organization and the use of the LALA Canvas model.

Workshop Held on August 18th, 2020, in San José, Costa Rica (Online)
This workshop was organized by SINAES, the national system for higher education accreditation in Costa Rica (https://www.sinaes.ac.cr/). This workshop organization was also supported by Laspau, and it intended to replicate the prior experience in Brazil. In this case, 154 people participated from different universities in Costa Rica, and 149 voluntarily answered a survey with a 4-point Likert scale to evaluate the overall quality of the workshop. Additionally, an open-ended question was included to evaluate the perceived usefulness of the LALA Canvas from a qualitative perspective. Answers to this question were inductively coded according to the coding scheme presented in Table 6.3. As in the first workshop, quotes were also extracted from participant's comments to illustrate the perceived usefulness of the LALA Canvas template.

Workshop Held on August 27th, 2021, in Lima, Perú (Online)
This fourth workshop was also conducted online, and it was part of the International Learning Analytics Program organized by the Pontificia Universidad Católica del Perú (in collaboration with LALA researchers and people analytics in

Table 6.3 Coding scheme to analyse open-ended questions from workshop participants in Costa Rica

Emerging code	Code description	Example (Participant's quote)
Needs for LA tools	Participant's comments regarding the potential use of LA tools and methods.	Learn about the various analytical tools and the steps of how to assess needs.
Understanding of LA	Participants comments about having acquired a better understanding of the LA concept.	I learned about the use of learning analytics to improve processes and services for students
LA for improving learning	Participants comments regarding the potential use of LA to improve student learning.	Learning analytics and its importance in the process of improvement and understanding of how our students understand and learn
LA for improving teaching	Participants comments regarding the potential use of LA to improve student learning.	These practices can also be used in teaching practices to develop educational research.
LA for improving decision-making	Participants comments regarding the potential use of LA to inform institutional decision-making.	I learned that learning analytics is an important and valuable tool for decision making.
Design of LA tools	Participants comments about having acquired a better understanding of the design of LA tools and methods.	I learned about learning analytics at a practical level concerning the development of a low or high-fidelity prototype.
Capacity building for data-based strategies	Participants comments about the importance of capacity-building for leveraging educational data.	It is important to start a process of convincing universities about LA adoption, taking concrete actions.
Technological infrastructure for LA deployment	Participants comments about the importance of improving technological infrastructure for LA adoption.	There is fragmented data in our institutions. It is important to be able to consolidate it and give it a use within the entities.

Perú — https://peopleanalytics.pe/). This program had two versions, one that involved 10 participants and one that involved 5 participants, and from both versions, 14 participants voluntarily answered a survey with a 5-point scale to evaluate the perceived usefulness of the LALA Canvas from a quantitative perspective. Specifically, we estimated the percentage of workshop participants who answered each item with a 4 or 5 to measure the perceived usefulness of the LALA Canvas. Workshop participants were also asked about the preferred order to address LALA Canvas components, and as in prior workshop surveys, quotes were also extracted from answers to an open-ended question in which participants could make comments about the workshop.

6.3 Workshop Findings Regarding the LALA Canvas Model

Table 6.4 summarizes the findings obtained from the series of workshops held between 2018 and 2020. These findings are based on the analysis of the survey responses obtained from each one of the workshops. As it is shown in Table 6.2, each one of these surveys aimed to assess and evaluate the perceived benefits and usefulness of the LALA Canvas model, along with other aspects related to the LALA Canvas workshop. The following sub-sections were organized to describe the results obtained from each workshop separately.

6.3.1 Results from Workshop Held in Chile, March 2018

Figure 6.4 shows survey responses about the perceived benefits of the LALA Canvas model. On the one hand, 15 out of 17 participants considered it very or extremely beneficial for reflecting on the need for tools based on LA in their institutions, which might imply that it is a good starting point for igniting discussions in early stages of LA adoption. On the other hand, 11 out of 17 participants considered it very or extremely beneficial for carrying out a diagnosis on the use of educational data and LA in their institution.

In these lines, Fig. 6.5 shows the frequency of mentions concerning the importance of LALA Canvas components from the perspective of workshop participants. Although all elements were selected as important for at least a couple of participants, there are two components that turned out to be the most relevant: desired behaviours and change strategy. Consequently, the LALA Canvas model was reorganized as presented in Fig. 6.6, organizing its components in the following order (this version was used in subsequent workshops):

1. Desired behaviours
2. Change strategy
3. Internal capabilities

Table 6.4 Main findings obtained from the series of LALA Canvas workshops implemented between 2018 and 2021

Workshop	Survey results	Supporting data
March 21st, 2018, Santiago, Chile	15 out of 17 workshop participants considered that the LALA Canvas was very or extremely beneficial for reflecting on the need for LA tools at an institutional level.	See Fig. 6.4
	11 out of 17 workshop participants considered that the LALA Canvas was very or extremely beneficial for carrying out a diagnosis on the current use of educational data and LA at an institutional level.	See Fig. 6.4
	Workshop participants suggested to reorganize LALA Canvas components, starting by defining desired behaviours.	See Figs. 6.5 and 6.6
May 28th, 2019, Lorena, Sao Paulo, Brazil	Most workshop participants agreed that the time allocated to workshop activities was distributed for a good understanding of LA (mean score of 5.92 out of 7), and that the activities were motivating enough to keep people engaged (mean score of 5.46 out of 7).	See Fig. 6.7
August 18th, 2020, San José, Costa Rica (online)	91 out of 122 participants perceived that the LALA Canvas model could be used to facilitate the understanding of LA (75% of coding references.	See Fig. 6.8
August 27th, 2021, Lima, Perú (online)	All workshop participants agreed or strongly agreed that the LALA Canvas model is useful for identifying key players in the use of learning analytics, and for formulating a change strategy for continuous improvement at an organizational level.	See Fig. 6.9
	Survey responses confirmed the adopted order of LALA Canvas components after the first workshop in Chile, excepting for the change strategy component (which could be address interchangeably with the component targeting influential actors).	See Table 6.5

4. Political context
5. Influential actors
6. Assessment and evaluation plan

"It is a strategy to identify those behaviours that need to be changed in the university community" (Data engineer).

"It presents a learning analytics adoption as a continuous improvement project" (Education technology professional).

"More concrete change goals that lead more directly to determining learning analytics needs" (Assistant director of instructional design).

"It allows you to identify existing databases and other type of resources that already exist in the institution" (Project director).

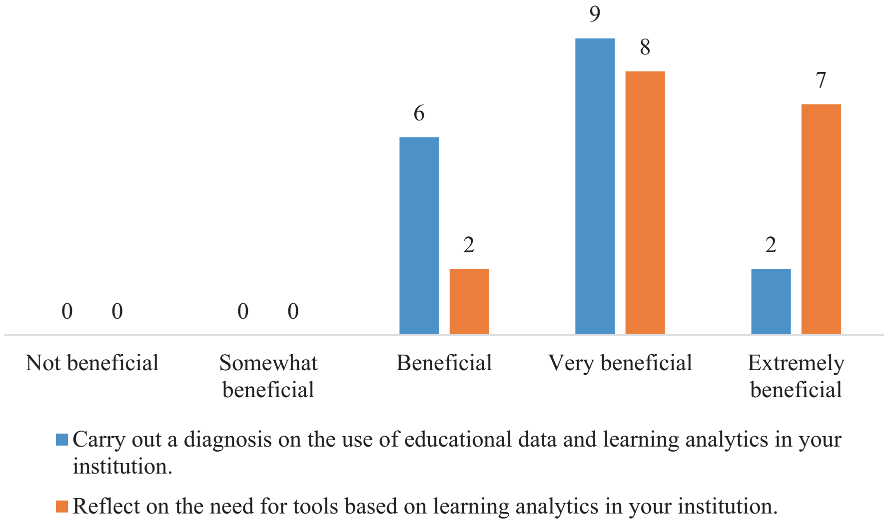

Fig. 6.4 Perceived benefits concerning the use of the LALA Canvas from the perspective of workshop participants ($n = 17$)

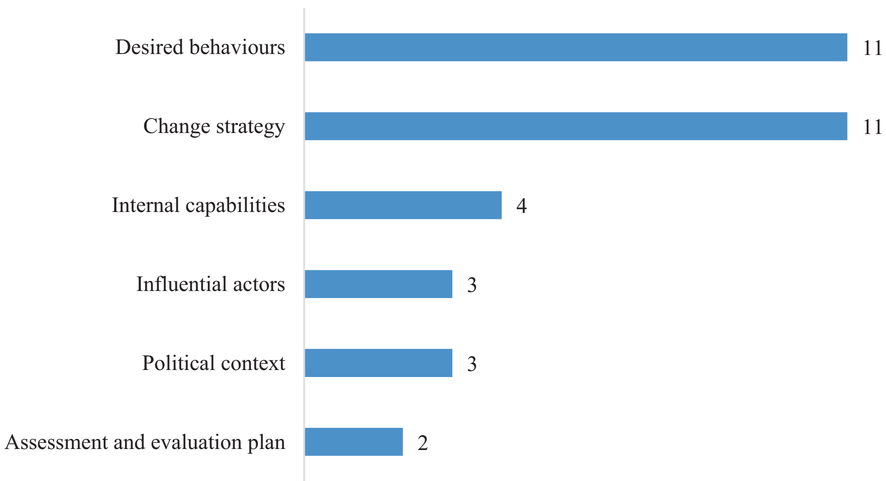

Fig. 6.5 Frequency of mentions concerning the importance of LALA Canvas components ($n = 17$)

6.3.2 Results from Workshop Held in Brazil, May 2019

Figure 6.7 shows the average level of agreement with different aspects related to the LALA Canvas workshop. One of the aspects in which most participants exhibited a higher level of agreement was concerning the time allocated to workshop activities,

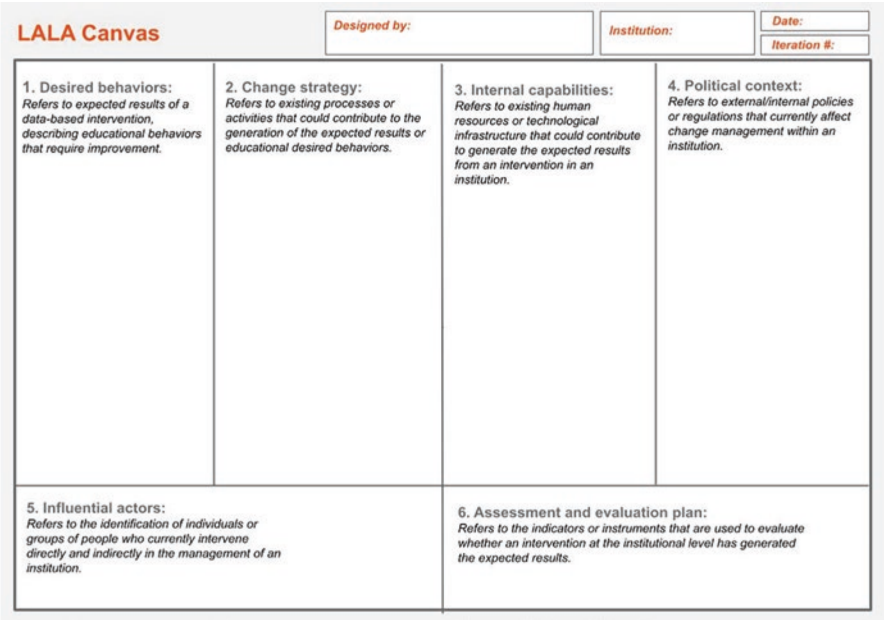

Fig. 6.6 Resulting LALA Canvas for further application in different educational setting Finally, the following quotes were extracted from workshop participants concerning the potential use of the LALA Canvas model in their institutions, revealing perceived benefits from professional and managerial roles within higher education institutions

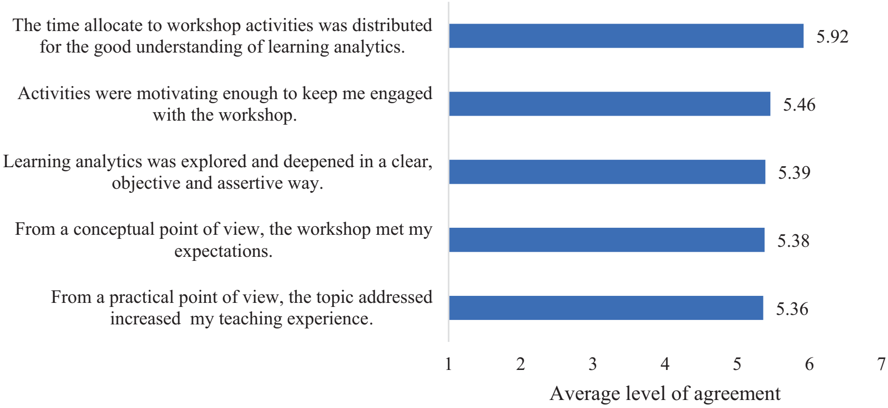

Fig. 6.7 Average level of agreement with different aspects related to workshop organization and the use of the LALA Canvas template (n = 122)

so that the participants could gain a better understanding of LA. Although the other elements also showed a high level of agreement, opportunities for improvement were formulated for future applications of the LALA Canvas, such as including more examples of tools and dashboard in the explanation of the LA concept.

6.3.3 Results from Workshop Held in Costa Rica, August 2020

Then, Fig. 6.8 shows the frequency of coding references considering participants' comments (see coding scheme in Table 6.3). It seems that most participants gained a better understanding of LA because of the application of the LALA Canvas. In these lines, further quotes were also extracted from participant's comments, which highlight the potential use of the LALA Canvas to present proposals and raise awareness among different higher education stakeholders:

> 'The LALA Canvas scheme is undoubtedly a very useful tool to advance specific proposals' (Workshop participant 1).
>
> 'I found the LALA Canvas to be phenomenal not only for organizing a proposal, but for simply presenting it to senior management' (Workshop participant 2).
>
> 'The LALA Canvas model will be very useful for me to sensitize my fellow deans, directors, and superiors' (Workshop participant 3).
>
> 'I found the LALA Canvas tool very interesting for the analysis and design of a system that allows displaying useful information' (Workshop participant 4).
>
> 'The first concept of excellent utility is the Lala Canvas. This tool, although it seems simple, is very helpful in identifying, planning, assessing, and implementing a process for improving learning' (Workshop participant 5).

6.3.4 Results from Workshop Held in Perú, 2021

Figure 6.9 shows the percentage of workshop participants who agree or strongly agree with different affirmations regarding the perceived usefulness of the LALA Canvas. All participants perceived it to be beneficial for identifying key

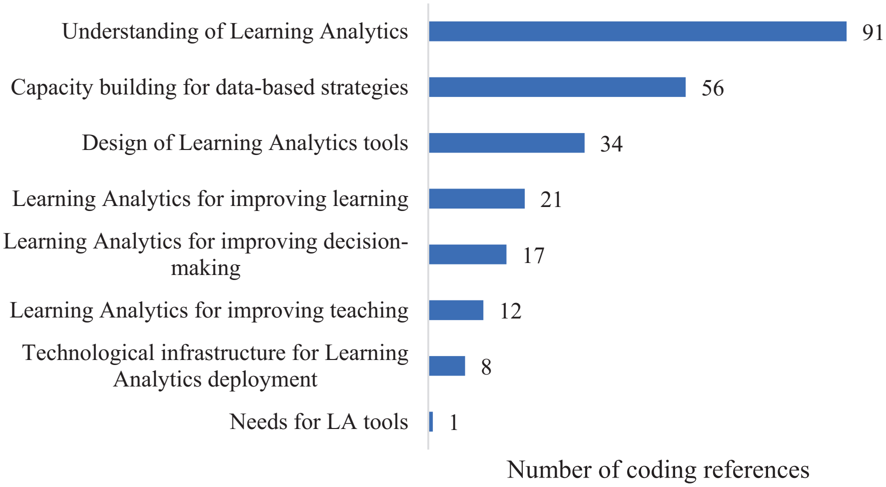

Fig. 6.8 Frequency of coding references regarding potential uses of the LALA Canvas model from the perspective of workshop participants (n = 122)

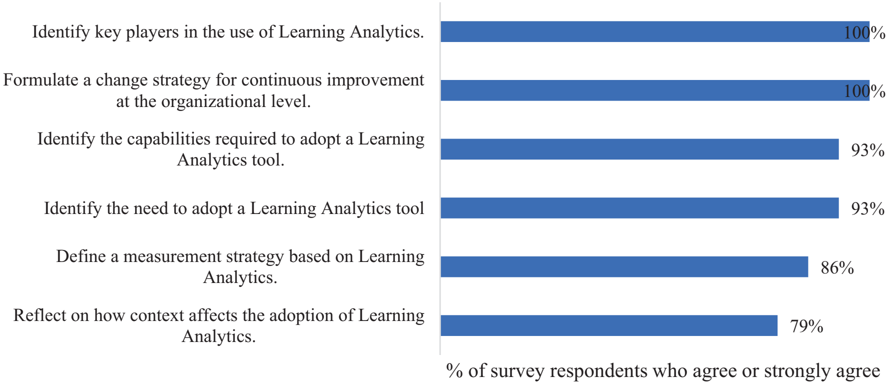

Fig. 6.9 Percentage of survey responders who agree or strongly with different statements about the perceived usefulness of the LALA Canvas model ($n = 14$)

Table 6.5 Statistics concerning participants' preferred order to address LALA Canvas components

Component	Current order	Mode	Min-Max
Desired behaviours	1	1	1–3
Change strategy	2	5	2–5
Internal capabilities	3	3	2–6
Political context	4	4	1–4
Influential actors	5	5	2–5
Assessment and evaluation	6	6	4–5

stakeholders and formulating a change strategy based on LA. Still, 93% participants also perceived it to be beneficial for identifying existing capabilities and the need for LA tools to address educational challenges (13 out of 14). In that sense, these results also account for the potential value of the LALA Canvas for starting conversations about LA adoption in universities whose maturity is still in an early stage.

Table 6.5 shows statistics concerning participant's preferred order to address LALA Canvas components. The mode shows that survey responses confirmed the adopted order after the first workshop in Chile for all except one component. This component is the one that suggests participants to list elements for a change strategy based on LA. It seems that some participants would have preferred to address this component after having listed elements concerning the desired behaviours, the political context, the internal capabilities, and the influential actors or key stakeholders. However, this was not a barrier for the LALA Canvas to allow participants to visualize potential needs for LA tools at their institutions. In these lines, the following comments were extracted from an open-ended survey question:

'This tool allows you to capture the information in a single view about the context, the needs and the strategies that must be implemented to use Learning Analytics in organizations. I believe that before moving on to this tool, a preliminary brainstorming and prioritization of the desired behaviours could be done. I am going to propose it within my design team to find concrete strategies that allow us to advance in the implementation of Learning Analytics in my organization' (workshop participant 1).

> 'It is a very useful tool to visualize the needs of adopting Learning analytics' (workshop participant 2).
>
> Besides, varied participants highlighted the usefulness of the LALA Canvas as a first attempt to determine a LA strategy, regardless of the order in their components are addressed:
>
> 'I find the tool useful to design the Learning Analytics strategy' (workshop participant 3)
>
> 'A good qualitative tool to define priorities and strategy for the team' (workshop participant 4).

6.4 Lessons Learned and Discussion

This section describes the lessons learned extracted from integrating and contrasting findings obtained from the series of workshops held in different Latin American university settings. First, workshop participants perceived the LALA Canvas to be beneficial to reflect on the need for LA tools in their institutions (see Fig. 6.4), gaining a broader understanding of LA (see Fig. 6.9). Within open-ended questions, participants also commented on the value of the LALA Canvas to raise awareness among different higher education stakeholders with respect to the potential of LA strategies to improve teaching and learning, including deans, directors, and other senior managers. Prior literature had already suggested that ROMA-based approaches could be an effective tool in higher education settings (Macfadyen et al., 2014), motivating different members of an educational community to exchange ideas about LA methods and tools. In the case of the LALA Canvas model, its components are good starting point for having conversations among higher education stakeholders, without necessarily having in-depth knowledge of what LA implies. Considering the limited availability of experienced LA researchers in some developing regions (Cechinel et al., 2020; Cobo & Aguerrebere, 2018; Lemos dos Santos et al., 2017), the LALA Canvas might be a valuable strategy for starting conversations in universities where LA adoption is still in an early stage.

Second, workshop participants highlighted the value of the LALA Canvas to identify key players in the use of LA (see Fig. 6.9). According to Khalil et al. (2022), few frameworks highlight the importance of university staff (e.g., student affairs), regardless of their contribution to support learning and retention. In the case of the LALA Canvas, workshop participants valued its potential use to get buy-in from institutional leadership and managers to formulate a change strategy (see Fig. 6.9). Through a one-hour discussion, the LALA Canvas might not only engage deans or program chairs, but also data engineers and Information Technologies (IT) professionals. Thus, this template could be used to engage leaders, faculty, and a wide variety of support staff in conversations about the current status of their institution in terms of LA adoption; generating a shared understanding of specific challenges and barriers that had to be overcome for making institutional transformation possible.

Third, one of the aspects in which most participants exhibited a higher level of agreement was concerning the effectiveness of time allocated to workshop activities, so that the participants could gain a better understanding of LA (see Figs. 6.7 and 6.8). According to participants' comments, several of them confirm that they gained a better understanding of LA because of the application of the LALA Canvas model, without necessarily requiring more than 30 minutes. Furthermore, from the series of workshops we were able to confirms the importance of the components that were included in the final version of the LALA Canvas model (see Fig. 6.5 and Table 6.5). This not only validates the LALA Canvas layout finally suggested (see Fig. 6.6), but also allows its use to be generalized in other contexts. Its use offers a rapid way to assess the current status of an institution in terms of LA adoption, without requiring prior knowledge about LA or an excessive amount of time.

Therefore, our main findings can be summarised as follows: the LALA Canvas is a useful model to formulate change strategies in higher education contexts where LA adoption is still at an early stage. Its application its cost-effective enough to ignite group discussions among different stakeholders in a short period of time. Although it might not be an exhaustive approach regarding the dimensions proposed by previous LA frameworks, it still covers the identification of the influential actors who could participate or benefit from the adoption of an LA tool or method in an everyday practice. Finally, this LALA Canvas model might motivate fruitful conversations to develop context-relevant and appropriate strategies to implement LA in developing regions.

6.5 Limitations

As in most studies, the lessons learned that are presented in this chapter are subject to the following limitations. First, surveys were jointly designed with organizations that collaborated with LALA researchers during workshop organization, and it was not possible to establish a single scale or question to compare findings over time. Second, the growth of the LA field is quite recent in Latin America, so further studies should be conducted in other regions for contrasting the results presented in this chapter. Third, there might be longitudinal effects of having engaged higher education stakeholders from different universities in conversations about LA adoption, but these effects were not observable during the LALA project timeline. During the development of the LALA project, we witnessed the adoption of LA tools in the Latin American partners (Guerra et al., 2020; Hilliger et al., 2020b, 2022; Ortiz-Rojas et al., 2019), but more time is required to examine further changes that might appear in the long-term as a result of discussions guided by the LALA Canvas model. Finally, most of the evaluations of the LALA Canvas model were conducted in Latin American Universities. Still, this model could be potentially used by any university interested in exploring the potential of LA for continuously improving student learning and program quality. In these lines, we expect to conduct future work in different regions, aiming to evaluate the perceive benefits and usefulness of the LALA Canvas model in a wide variety of contexts.

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Chapter 7
How Learning Process Data Can Inform Regulation in Collaborative Learning Practice

Sanna Järvelä, Eija Vuorenmaa, Ahsen Çini, Jonna Malmberg, and Hanna Järvenoja

7.1 Introduction

Computer supported collaborative learning (CSCL) has been implemented as part of various teaching and learning models, face-to-face, on-line and hybrid, at different educational levels and in work-life teams. Global changes in educational landscape are pushing a need for empowering learners as agentic participants in communities of learners (Rosé & Järvelä, 2020). Collaborative learning (CL) is a powerful way of enhancing individual learning and can also be effective in developing group working skills and practices. The social construction of knowledge is commonly made via collaborative efforts through dialogues and interactions and facilitated by differences in persons' perspectives (Roschelle & Teasley, 1995).

Transactive activities play a crucial role in CL (Kirschner et al., 2018). Learning is likely to occur in these synchronous and asynchronous activities when the collaborating students engage in transactive discourse, such as criticizing, challenging positions, and making mutual thoughts via discussion, because this form of discourse gives rise to cognitive activities that stimulate knowledge construction (Popov et al., 2017). Still, CL effort is influenced by how well students coordinate their activities across time and transact with each other's ideas (Schwartz, 1995). This is where regulation of CL plays a role.

Effective CL requires group members to ensure that they work toward the shared goals and reveal to each other when they become aware that their collaboration is not heading toward the shared goals. In successful cases, learners negotiate shared

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goals to ensure they all work toward the same outcome (Järvelä et al., 2018), maintain a positive socioemotional atmosphere to ensure fluent collaboration (Lajoie et al., 2015), and finally, coordinate and ensure that each member is responsible for the joint outcome of their collaborative task (Lin, 2018).

Socially shared regulation in learning (SSRL) (Hadwin et al., 2018) development has been guided by Winne and Hadwin's (1998) model, which describes self-regulated learning (SRL) as a cyclical feedback loop where metacognition is an "engine" that operates in the process of learning and activates regulation. SSRL empowers individuals and peers to have successful collective participation in groups and affords their collective agency and goal setting, proactive skill training for individual adaptation, and working in teams, as well guidelines for leveraging technologies for supporting human learning (Järvelä et al., 2021).

We have been studying when, how, and what makes regulation in CL functional, aiming to understand the process of collaboration so that we could better inform learners and teachers in practice. Understanding regulation in CL is still a challenge. Firstly, regulation in learning is a complex metacognitive level mental effort and, therefore, difficult to capture (Malmberg et al., 2019). Secondly, regulation in CL is a temporal and sequential process that needs to be characterized to guide participation timely and facilitate interactions (Vogel et al., 2022). Because there is more data available in today's digitalized tools and educational environments that could be leveraged to understand self-regulated learning process (Nguyen et al., 2021), computational methods and learning analytics (LA) allow us to study tendencies and patterns which help to characterize temporal processes of some core phenomena (Cukurova et al., 2018).

To understand the complex process of regulation in CL, we have been working by gathering and analysing multimodal data about self-regulated learning with intelligent learning technologies (Järvelä et al., 2021). Several data modalities from different channels have been collected to investigate the cognitive, metacognitive, emotional, and social processes related to learning regulation at both individual and group levels. These data include, e.g., tracking logs, video, audio, and physiological data such as electrodermal activity (EDA) and heart rate. With interdisciplinary efforts (Järvelä et al., 2020) we are progressing with the alignment between theoretical notions, data structures, and methodological assumptions underlying techniques used to analyse the data (Dindar et al., 2022).

Our research has shown that the role of metacognitive monitoring in CL is pivotal (Haataja et al., 2021). Metacognitive monitoring is always an internal mental process, but in collaborative situations, it can be externalized and possibly shared via interactions with other group members (Dindar et al., 2020b). The aim of this chapter is to discuss metacognitive awareness and participation in cognitive and socio-emotional interaction as essential aspects to support, while being the complex processes in CL. Collecting multimodal data about these processes and implementing LA can simplify the complex phenomena for researchers to understand and provide practical help to learning and teachers.

7.2 What Makes Regulation in Collaborative Learning Complex?

Collaborative groups can be considered systems where the cognitive, emotional, motivational, and behavioural states of the group and its' members are related to each other and in constant flux. In group interactions, the experiences of group members and the interpretations they give to the interactions frame the unique group dynamics (Järvenoja et al., 2013; Rogat & Adams-Wiggins, 2014). Understanding regulation in these collaboration settings requires comprehending their multifaceted relations not only between cognition, emotions, and motivation that take place while a group of people collaborate to learn, but also in relation to individual group members' personal history, experiences, and attitudes (Boekaerts & Pekrun, 2015; Järvenoja et al., 2018). For example, affective reactions in a learning situation build on and are built upon the cognitive appraisals and motivational beliefs individuals assign to situations (Frijda et al., 2000; Shuman & Scherer, 2014).

What makes CL particularly complex is the social context and interaction that constantly (re)shape the social plain for collaboration and individual appraisals. Previous research has addressed collaboration from different angles showing, for example, how affective states fluctuate throughout the learning situation in relation to social interactions (Bakhtiar et al., 2018; Pijeira-Díaz et al., 2019; Törmänen et al., 2021), and how group members construct knowledge together in constant exchange through negotiation and sharing of knowledge (Hmelo-Silver & Barrows, 2008; Kreijns et al., 2003; Mitchell et al., 2014; Scardamalia & Bereiter, 2014). All these different processes are essential for successful collaboration, and regulation of them is vital when these processes are jeopardized (Hadwin et al., 2018). Moreover, regulation in CL contexts is temporally alternating (Lee et al., 2014), calling evidently multimodal data to unpack the reasons, processes, and consequences of coordinated group regulation for overcoming challenges and adapting learning and interaction to progress with their goals (Azevedo et al., 2016; D'Mello et al., 2017; Sobocinski et al., 2017). Previous studies have provided preliminary evidence of how progress in CL requires conscious regulation of cognition, behaviour, and affect at both individual and group levels, targeting, for example, temporal fluctuation and sequential relationship of co- and socially shared regulation of cognition, emotions, and motivation (Fischer & Järvelä, 2014; Molenaar & Chiu, 2014). These results emphasize the focal role of metacognitive awareness between the group members.

7.2.1 The Role of Metacognition in Awareness of Regulation Needs

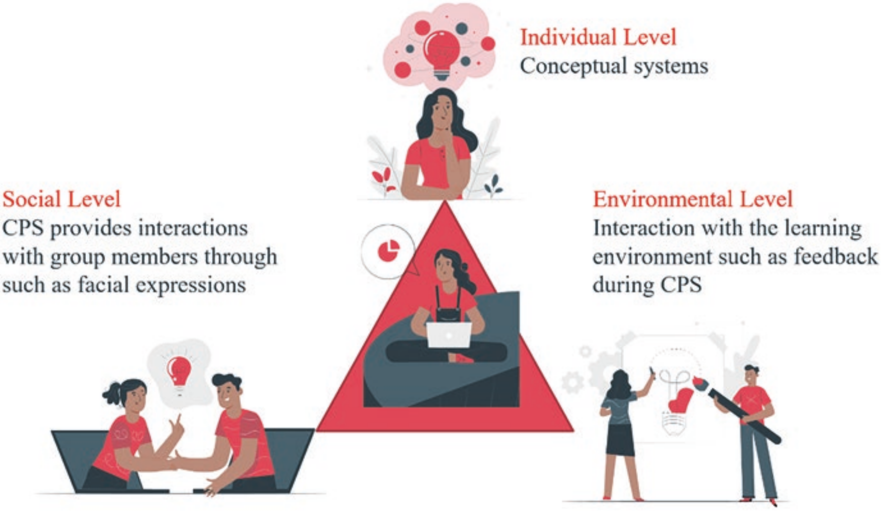
Metacognition enables students to determine weaknesses that can be addressed and regulated. Therefore, metacognition and especially building on metacognitive awareness enhance students' abilities for better regulation (Schraw, 1998). In the context of CL, learners can externalize their thinking processes and make their metacognition visible by sharing their thoughts on a social plane (Hadwin et al., 2017). Earlier research has shown that, for example, students' views of their task perceptions might vary which might lead to different views in terms of how the collaborative task should be done and how it should look like (Bakhtiar et al., 2018). In addition, when perceptions of task understanding are shared in the context of CL group members gain information not only about their own perceptions for learning, but also those of other group members. Therefore, externalizing perceptions of task understanding can be informative when guiding regulation of learning and inviting group members for socially shared regulation of learning (Iiskala et al., 2011). Students find the task easier and they understand it better once their CL has progressed and their content knowledge has increased (Çini et al., 2020). These findings align with SRL theory (Winne & Hadwin, 1998) which explain that regulation involves a cyclical loop, which allows learners to define and re-define their evolving understanding of the task as they co-construct interpretations of the collaborative task by externalizing their metacognition (Malmberg et al., 2017; Miller & Hadwin, 2015).

While students can be metacognitively aware of their cognition, motivation, emotions, or behaviour (Hadwin et al., 2017), it is possible that they do not even recognize the need for regulation (Malmberg et al., 2015). For this reason, there has been a body of empirical research that has developed ways and methods to increase metacognitive awareness. Despite the methodological progress in the field of education, the field still struggles to promote metacognitive awareness timely. Because of that, there has been a growing tendency toward using LA and Educational Data Mining (EDM), especially in the field of SRL (ElSayed et al., 2019). The premise of LA in the field of education is that, for example, the data resulting from on-line learning systems can be used to predict the learning outcomes (Di Mitri et al., 2017), recognize traces or processes of various learners (Jovanović et al., 2017), or enable learners to reflect about their actual learning activities (Poitras et al., 2017). Ultimately, the purpose of LA or EDM is to develop new ways to support learners to develop their SRL by in various contexts by providing scripts, prompts or guidance for learning processes. For example, Sonnenberg and Bannert (2015) investigated how applying metacognitive prompts affect learning performance and the appearance of phases of regulated learning. They found that metacognitive prompts assist not only with the learning performance but also that compared to low-performing students, high-performing students showed more frequent changes between phases of regulation, such as planning and task enactment. Similarly, a study by Malmberg et al. (2017) showed that metacognitive monitoring promoted task enactment, which eventually provided grounding for socially shared regulation to occur.

Earlier work promoting metacognitive awareness has focused on planning and reflection tools for prompting individual and group planning and reflection processes (Sonnenberg & Bannert, 2019; Hadwin et al., 2018), providing visualisations of individuals and group members emotional, cognitive, and motivational states (Järvelä et al., 2016b; Phielix et al., 2011) or prompting collaborating group members to collectively think how the group could enhance their cognition, motivation of emotions in their CL (Vogel et al., 2022; Järvenoja et al., 2020). These awareness tools have been designed to support regulation by prompting learners and groups to increase awareness of their own, others', and their group's metacognition and externalise their own, others', and their group's learning processes in a social plane, and activate key regulation processes, such as setting goals, making plans, adopting strategies, and monitoring and evaluating. Promoting metacognitive awareness begins with building awareness among learners that metacognition exists (Schraw, 1998). Learners are not often aware of challenges that occur during learning, and therefore learners' ability to engage in metacognitive monitoring is a key to successful regulation (Winne & Hadwin, 2008). However, metacognitive monitoring might be misleading if learners cannot connect what they think they are doing versus what they did (Winne & Jamieson-Noel, 2002). In such scenarios, for example, LA or traces collected from on-line learning system could help learners to accurately reflect their activities and how those activities relate to performance. Recently Vogel et al. (2022) examined the effects of adaptable scripts in the context of CL. What their study results showed, was that scripts were partly helpful for students with higher levels of self-regulation skills. This is to say, the ways how support is provided for the learners depends on their SRL and metacognitive awareness.

7.2.2 How Multiple Levels of Metacognitive Awareness Operate in Collaborative Problem Solving

Since metacognitive awareness is "thinking about your thinking" and learning developing "introspection" that can be facilitated by external sources in addition to internal ones. When individuals work in collaborative groups, they evaluate their own and group members' ideas through task processing and activating their metacognitive awareness (Hurme et al., 2009). In other words, metacognition is an individual process, but it cannot be explained exclusively by individualistic conceptions, especially in a collaborative group context (See Picture 7.1). At the *individual level*, the sources of metacognitive awareness are the conceptual systems of individuals (Lesh & Doerr, 2003). For example, we can regulate and control our learning with planning, monitoring, information management skills, and evaluation. At the *social level,* the sources of metacognitive awareness are one's interaction with others (Taub et al., 2021). In practice, interactions with peers and teachers, students can be encouraged to retest their current thinking, monitor their current level of knowledge and understanding, and detect and correct their misconceptions. For example, consider a collaborative problem-solving task, which provides sharing knowledge construction through interactions in written and spoken language, body movements, facial expressions, and manipulation of the task conditions by the computer. At the *environmental level*, metacognitive awareness sources are the one's interaction with the learning environment, such as classroom activities, task complexity/difficulty, stages of problem-solving, and multiple cycles of feedback, where students criticize and revise each other's thinking (Kim et al., 2013).



Picture 7.1 Multiple levels of metacognitive awareness

While metacognition has been traditionally studied with rather a static approach, e.g., self-reports, different kind of data and analytics could be used to understand multiple levels of metacognitive awareness, and more ways to facilitate, support and train metacognitive awareness in practice could be developed. Çini et al. (2022) studied how metacognitive awareness at individual, social and environmental levels is associated with collaborative problem solving (CPS) task performance and related to facial expressions. Seventy-seven higher education students collaborated in triads on a computer-based simulation about running a fictional company for 12 simulated months. Both static and dynamic measures were used in this study, such as traditional questionnaire, situated self-reports, and facial recognition implemented from video data to reveal multiple levels of metacognitive awareness in a collaborative context. The individual level of metacognitive awareness was measured with Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994). The sources of metacognitive awareness at the social level, i.e., metacognitive judgements and the perception of task difficulty, were measured through situated self-reports applied during collaboration multiple times. Finally, a complex CPS process with multiple feedback provided during the simulation-based CPS task ensuring the learners a place to implement, develop and provoke various metacognitive processes was used to measure the environmental level of metacognitive awareness. Group members' interactions for 96 min (SD 28.08) collaboration was further video recorded. Perceived individual and group performance were measured with self-reports at the end of the CPS task. A structural equation modelling (SEM) was conducted to observe the relationships between the multiple levels of metacognitive awareness and CPS performance. In addition to that, three-level multilevel modelling was used to understand the effect of environmental source of metacognitive awareness in the CPS environment.

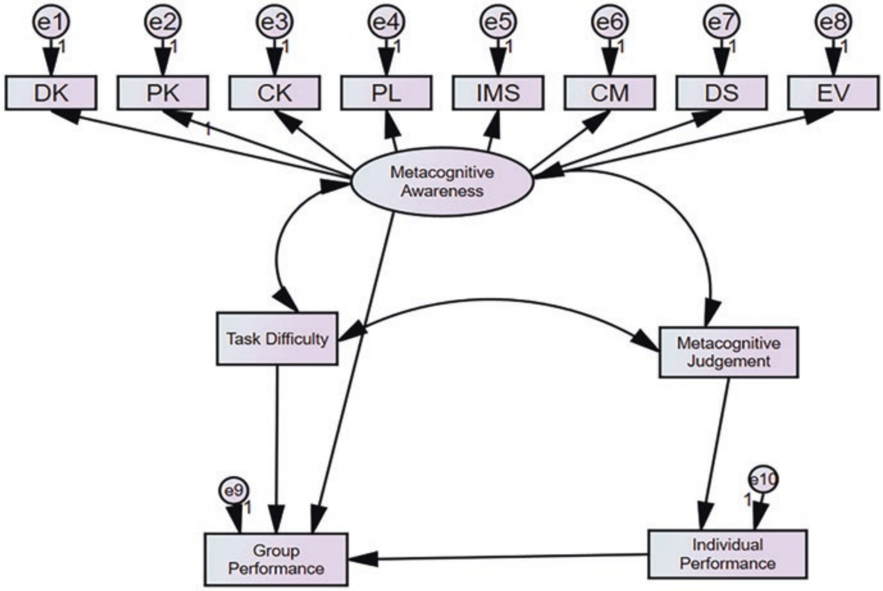


Fig. 7.1 Structural Equation Model (SEM) of relationships between multiple levels of metacognitive awareness and performance. (From: Çini, A, Järvelä, S, Dindar, M & Malmberg, J 2022, 'How multiple levels of metacognitive awareness operate in collaborative problem solving [Manuscript under preparation]', Learning & Educational Technology Research Unit (LET), University of Oulu. Note. *DK* declarative knowledge, *PK* procedural knowledge, *CK* conditional knowledge, *PL* planning, *IMS* information management strategies, *CM* comprehension monitoring, *DS* debugging strategies, *EV* evaluation)

The structural equation analysis was conducted to test the effect of individual and social levels of metacognitive awareness on perceived individual and group collaborative performance at an individual level (See Fig. 7.1). In addition to that, three-level multilevel modelling was used, which provides a useful framework for thinking about problems with this type of hierarchical structure: Level 1 (time: participants' responses to the metacognitive judgement and task difficulty questions and their facial expressions at the feedback times); Level 2 (individuals) and Level 3 (groups in collaborative learning). In all sub-questions, the dependent variable is feedback.

Çini et al. (2022) study indicates that the sources of metacognitive awareness at individual and social level predict collaboratively perceived group performance. Earlier research shows that learners' individual metacognitive awareness does not predict learning outcomes at an individual level (Çini et al., 2020). However, this study extended earlier research and examined the effects of different aspects of metacognitive awareness to collaborative performance and found a direct effect from individual metacognitive awareness to perceived group performance at an individual level. Similarly, Dindar et al. (2020a, b) highlighted the importance of metacognitive experiences in successful CPS. Also, this study contributes it via focusing on feedback as an environmental source of metacognitive awareness to understand more about metacognitive awareness in CL specifically in CPS. According to three-level multilevel modelling, feedback predicts metacognitive judgements and facial expressions in the CPS environment but does not predict the perception of task difficulty. A closer look at the results of the relationship between feedback and facial expression and metacognitive judgement indicates that facial expressions are indicators of judgement of confidence. In other words, facial expression recognition makes visible these and, thus, can add a new data channel and methodological means to understand metacognitive awareness.

This study shows the importance of metacognitive awareness for CPS since the results indicate that interaction with the learning environment is a potential source encouraging students to develop metacognitive ability. These interactions help students unpack misconceptions and repair them through metacognitive processes operating at both the individual and social levels. In collaborative contexts such as CPS, students often have difficulties evaluating their own solutions, but peers can help with this evaluation. They evaluate each other's ideas, serving a metacognitive role for one another (Goos et al., 2002; Hurme et al., 2009) via facial expressions, as was seen in this study. Some other studies show the importance of facial expression for intelligent tutoring systems for practical help in student metacognitive awareness. For example, estimating student's perception of lesson difficulty and student's preference about lesson's speed while watching it (Whitehill et al., 2008). Çini et al. (2022) study add that if multiple level of data and advanced analytics are implemented novel awareness tools/tutors that support effective collaboration during complex problem solving can be developed by studying different aspects of metacognitive awareness.

7.2.3 Implementing Process Mining to Characterize the Role of Participation in Cognitive and Socio-emotional Interactions for Regulation

As noted, regulation plays a role in adaptive process of CL (e.g. Sobocinski et al., 2017). Previous research also reports about the sequential patterns of regulatory processes, such as patterns and strategies in students' self-regulation (Bannert et al., 2014) or sequential interconnection between regulation and cognition in collaborative learning (Molenaar & Chiu, 2014). As CL evolves over time in social interactions among learners (Kirschner et al., 2018), investigating patterns in regulatory processes as such may not be enough to understand the role of regulation in CL, but more is needed to know about what kinds of interaction patterns may precede or follow regulation in context. Characterizing the role of learners' participation in these processes will add, since it acts as a key mechanism in collaboration. For example, favourable participation is known to enhance group productivity and learner achievement during collaboration (Cohen, 1994), whereas problems in participation (e.g., some group members invest little to no effort in group work) can hinder collaboration (Karau & Wilhau, 2020). Participation refers to learner's contribution to verbal communications and interactive exchanges in the group (Clark & Brennan, 1991) and it plays a role in cognitive interaction, enabling learners to discuss and analyse their domain-focused content knowledge (Baker, 1999), as well as in socio-emotional interaction, through which learners can share their emotions and build group's socio-emotional climate (Sinha et al., 2015).

Previous research has suggested that regulation of learning may relate to how individual learners or group participates in collaborative interactions, and highlighted, for example, equal participation (Grau & Whitebread, 2012), all group members' contribution (Iiskala et al., 2015), and active and cohesive interactions (Sinha et al., 2015). However, these studies still have not been able to explain the temporal processes or relations of regulation, interactions, and participation. If we understood more about the time-related patterns of these processes, more could be learned about how and when to support collaborative groups in their interactions so that they facilitate regulation of learning when needed. We have implemented process mining to reveal how regulation emerges in time-related cognitive and socio-emotional interaction processes during collaborative learning. Process mining aims is to discover, monitor, and advance real-life processes by using information from event logs. It utilizes sequentially recorded events where each event represents an activity that is related to a certain case (van der Aalst, 2011), and generalized visualization of the sequences, their interconnections, and patterns are represented in a process model (Reimann et al., 2009). While process mining techniques are traditionally used in computer science, they can also be utilized in educational context to explore learning processes, such as regulation of learning (Bannert et al., 2014). The value of utilizing process mining in educational context is that it can discover the most dominant real-life processes that the learner(s) or small group(s) engage in during a certain learning process, which can help in recognizing, for example, what kind of group interactions may enable or hinder regulation of learning. Next, we introduce in more detail how process mining was used in our research to reveal favourable participation and interaction patterns for regulation in CL context.

Vuorenmaa et al. (2022) investigated the sequential patterns in groups' social interactions for group-level regulation during CL tasks. The participants were secondary school students (N = 92, 29 groups of three to four students) performing various collaborative light and sound related tasks during a physics course. The data collection was implemented in the students' own classroom, where the student groups were videotaped for five 90-min sessions over 8 weeks. In all, 175 h and 30 min of video recorded data were analysed with Observer XT12 data analysis software regarding participation, cognitive and socio-emotional interactions, and co- and socially shared regulation (i.e., group-level regulation) (Bakhtiar et al., 2018; Hadwin et al., 2018; Järvelä et al., 2016a, c; Rogat & Linnenbrink-Garcia, 2011). For the participation, interaction, and regulation coding, the video data were divided into 30-s sequences since it was long enough to include relevant interactions, enable detailed observations, and make valid judgments of behaviour. The coding categories were not mutually exclusive and could occur parallel to each other in different combinations. Based on the interactivity coding, three social interaction states were defined in the sequences: simultaneous cognitive and socio-emotional interaction (COG & SOC-EM), cognitive interaction (COG), and socio-emotional interaction (SOC-EM). Two participation levels, whole group (WHOLE), and partial group (PART), were identified in the sequences, characterizing the intensity of groups' participation in the interactions. After this, the concurrence between group-level regulation types and social interaction states (including participation level) was investigated. The analysis was continued by utilizing process mining with the help of Fluxicon's Disco analysis software (https://fluxicon.com/disco/) to investigate the sequential interaction and participation patterns for group-level regulation in CL. This was done by using the 30-s sequences before, during, and after each observed group-level regulation sequence. Since process models can illustrate each possible interconnection and path of extremely complex real-life processes, the models require simplification (Dolak, 2019; Malmberg et al., 2015). Thus, it was decided to focus on the most frequent emergence of group-level regulation in social interaction states and participation levels. The level of activities and paths was restricted to show only the strongest, most frequent paths of interconnectivity. However, the sequences before and after regulation were not restricted in terms of regulation, interaction, or participation, allowing all possible combinations of these facets to emerge in the preceding and following sequences of regulation. These procedures enabled us to find the strongest patterns for regulation in a relevant interaction state. Figure 7.2 presents an example of a process model dealing with collaborative interactions and regulation by characterizing the strongest patterns between social interaction states and SSRL. It demonstrates that the SSRL episode most frequently started with a state of simultaneous cognitive and socio-emotional interaction with whole group participation (COG & SOC-EM & WHOLE, f = 48), and was followed by SSRL in the same interaction state (f = 68 for occurrence and f = 24 for path), again continuing with simultaneous interaction and whole group participation (f = 26 for path).

The example in Fig. 7.2 shows how SSRL emerged the most frequently, when the groups' collaboration included both cognitive and socio-emotional interaction on a whole group participation level. Overall, Vuorenmaa et al. (2022) results highlight how regulation of learning, which is fuelled by metacognition, is related to cognitive processes that can be captured through cognitive interactions in group settings. However, in collaborative settings regulating merely cognitive processes is not sufficient, since learners in groups can experience a range of emotions regarding for example the task, other group members or the group's joint strategies (Lobczowski, 2020), thus, the interplay of both cognitive and socio-emotional interactions during SSRL process can be seen in the example. Implementing learning process analytics, as the process model in this example, can elaborate the earlier findings, which have highlighted that SSRL is a jointly constructed group-level process which requires reciprocal exchanges between learners (Iiskala et al., 2015; Järvenoja & Järvelä, 2013). It can be seen from the example, that SSRL not only emerges the most frequently, when the whole group is actively engaging in cognitive and socio-emotional interactions, but similar participation and interaction processes also precede and follow SSRL. These kinds of results that reveal time-related

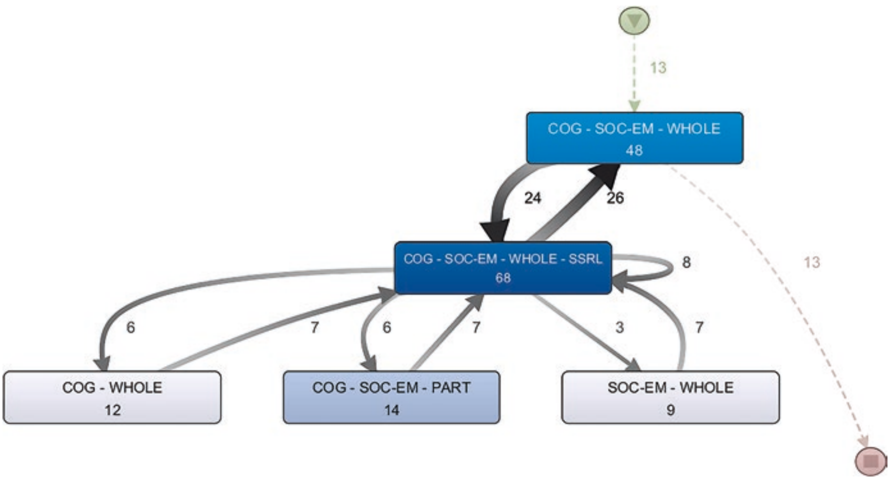


Fig. 7.2 A process model illustration of SSRL episodes. (From: Vuorenmaa, E, Järvelä, S, Dindar, M & Järvenoja, H (2022), 'Sequential patterns in social interaction states for regulation in collaborative learning', Small Group Research)

interaction processes in CL can help in defining characteristics of participation in social processes that can facilitate SSRL during collaborative process. With this understanding for example teachers can plan their CL designs to give more adequate and timely support to learners in small groups so that they can engage in cognitive and socio-emotional interactions, proceed with the task collectively, and maintain a positive socio-emotional group climate. Receiving timely support for cognitive and socio-emotional processes can eventually help learners to learn how to adapt in continuously changing learning situations.

7.3 Conclusions

Decade of research on regulation in CL has shown that regulation is a crucial process for making the maladaptive process of CL more adaptive (Järvelä & Hadwin, 2013; Volet et al., 2009). MMLA are showing promise to reveal new understanding of the temporal and sequential aspects of regulation in CL (Saint et al., 2022) in designing and utilizing various learning technologies and tools to support regulation in learning and tailoring just-in-time support for teachers and learners (Martinez-Maldonado, 2019).

When considering CL as a temporal, social interaction process, understanding the patterns of the type of social interaction (e.g., Vuorenmaa et al., 2022) can explain what are the targets that need regulation, whether it is cognitive processes, socioemotional conflicts, or motivational problems. For this MMLA can provide many new means, for example, measuring the intensity of students' CL from their observable interactions as Cukurova et al. (2020). They used video data and bodily gestures to measure students' CL showing that the nature of the bodily gestures, such as hands distance and distance between collaborating group members' faces predicted collaborating groups learning outcomes. Similarly, Tang et al. (2022) used video data to investigate quality of CL and electroencephalogram (EEG) to measure students' attention. Their study revealed that intensity of attention was related to learning outcomes and especially in CL situations where students' collective efforts we aligned between the group members. In addition, Malmberg et al. (2019) measured occasions of physiological synchrony from collaborating groups EDA and verified from the video data what actually happens in those situations. This study revealed that in those occasions the students struggled with the learning task.

Empirical research and conceptualisation of regulation in CL calls a need for teachers or other intelligent systems to monitor student collaborative interactions and intervene so that support for metacognitive awareness, active and reciprocal interactions can be provided when needed (Strauß & Rummel, 2021). Interactions with and about "metacognitive awareness" can help practitioners in recognizing problems during the learning process that may hinder regulation and help in reacting to them appropriately at an early stage. Çini et al. (2022) study suggest that with the help of multiple level of metacognitive awareness data, systems could be created when students are having trouble understanding the tasks. Further studies can help identify the optimal design of awareness tools to prompt both metacognitive awareness and SRL skills. It is also important to keep in mind that the field of MMLA is still in its early stages and requires in details operationalisation and empirical research to utilize its potential in education (Alwahaby et al., 2022).

Collecting multimodal data and implementing learning process analytics has helped us to proceed in our SSRL research so that both inductive and deductive analyses have complemented our understanding about metacognitive level components in regulation and social interaction processes in collaborative learning. While detailed qualitative analyses have uncovered contextual interactions, process models have revealed patterns, sequences, and regularities. For example, capturing participation and social dimensions in collaboration through social network analysis could add to understanding student participation (Saqr et al., 2020). Currently, we aim to investigate how machine learning techniques could be implemented to examine the multiple facets and processes of regulation in learning. For example, Nguyen et al. (2022) used the artificial intelligence (AI) deep learning approach on multimodal data to detect regulatory interactions for successful and less successful groups in CL, hence predicting and supporting CL success.

In today's education, digital tools will have much data available and with the help of LA and AI-based methods we can create a deeper understanding of the learning process. More these sources of data can provide means for researchers to examine the frequency, timing and sequence of regulatory traces situated in authentic learning activities to identify learners or teams that might be struggling and provide timely intervention or prompts to deploy regulatory strategies as needed.

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Chapter 8
Learning Analytics Education: A Case Study, Review of Current Programs, and Recommendations for Instructors

René F. Kizilcec and Dan Davis

8.1 Introduction

The interdisciplinary field of learning analytics emerged in 2008 and quickly grew into a global community of researchers, practitioners, and educators who have made important scientific and applied contributions (Clow, 2013; Siemens, 2013). Journals, conferences, workshops, and informal online outlets such as blogs have served as venues for knowledge exchange, co-creation, and inspiration. As the field matures, institutions of higher education increasingly offer courses, certificates, and degree programs in learning analytics to disseminate the theories, methods, applications, and values of this field. These educational programs help train the next generations of leaders in learning analytics research, practice, and policy. They also encourage more people to work in areas related to learning analytics, especially those looking to combine an interest in data science and technology with a desire to effect positive change in society. These efforts to teach and learn learning analytics in formal and informal educational environments are the focus of this chapter. We begin with a survey of the landscape of current learning analytics programs and examine what topics and pedagogies are represented. This is followed by an in-depth case study of a learning analytics course offered to undergraduate and graduate students at Cornell University. The case study demonstrates a pedagogical approach to learning analytics education for students with a more technical emphasis. Finally, we discuss the current state of learning analytics education and identify challenges and opportunities for learning analytics education going forward. This

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chapter contributes to practicable learning analytics by providing evidence on the status quo of teaching and learning learning analytics with a comprehensive review of current learning analytics programs and a case study of a university course, and by offering a set of actionable guidelines for the community to consider when designing learning analytics courses.

Learning analytics education has a wide range of audiences and objectives. Students, teachers, instructional designers, parents, professional student advisers, and school leaders are increasingly likely to interact with or be affected by learning analytics models and applications. They can benefit from understanding the assumptions, data inputs, engineering and design choices underlying these models and applications. It helps them make informed judgments about the relevance and appropriateness of different learning analytics for their use case and the kinds of inferences they can draw from the information to inform their actions and policy decisions. There are also important audiences outside of traditional formal education environments with a stake in learning analytics education. The growth of interest in lifelong learning and demand for continuous skill development in the labor market has elevated the role of professional development. Working learners need to make decisions year after year about which formal or informal educational opportunities to pursue and whether they are effectively learning the knowledge and skills they need. Human resource departments, which tend to oversee professional development programs and policies, need to make informed decisions about which learning opportunities to offer or incentivise, and how to evaluate employees' learning outcomes and their downstream effects on performance at the intersection between learning analytics and people analytics (Tursunbayeva et al., 2018). In some high-stakes work environments, such as aviation, medical, and military contexts, precise training and assessment analytics have already been in use and other work environments are eager to adopt a targeted approach to professional development with learning analytics. Given this wide range of audiences with varying objectives for learning about learning analytics, there is not just one right learning analytics curriculum for everyone as illustrated in our survey of programs and the case study.

The field of learning analytics keeps evolving, building on expertise from various scientific disciplines, and its applications are integrated into more and more real-world contexts with different domain-specific knowledge and skills. Learning analytics is grounded in the learning sciences, including cognitive science, social and educational psychology (Sawyer, 2005), and in the computational social sciences, including computer and data science, network analysis, data visualization, and statistics Lazer et al., 2009. Learning analytics research and practice relies on combinations of theory and methodology from these two clusters of disciplines. Early adoptions of learning analytics applications prompted questions about ethics and privacy, which has started to bring in disciplinary expertise from law, sociology, public policy, and critical studies. Moreover, domain experts are frequently involved in domain-specific learning analytics to provide context and address particular issues in that domain. Altogether there is a diversity of disciplinary backgrounds represented and engaged in collaborations in learning analytics events and organizations; for example, the Educational Data Mining Society and its International

Conference on Educational Data Mining (EDM; started in 2008), the Society of Learning Analytics Research (SoLAR) and its International Conference on Learning Analytics and Knowledge (LAK; started in 2011), and at the ACM Conference on Learning at Scale (L@S; started in 2014). The interdisciplinary nature of learning analytics suggests that a curriculum for learning analytics can be offered by various departments and organizations, not only schools of education. This point is illustrated both in our case study course, which is offered by the College of Computing and Information Science, and in our survey of the learning analytics education landscape, which identifies multiple different departments offering learning analytics programs. The next section provides an overview of educational offerings in the field of learning analytics.

8.2 The Learning Analytics Education Landscape

We conducted a review to understand the landscape of educational offerings for learning analytics with a focus on the types of programs and institutions offering them. The goal of this survey is to highlight trends in the geography of institutions, disciplinary homes, and types of current learning analytics programs. We used the following methodology to arrive at the list of current programs. Two search strategies were employed to identify relevant programs: (1) Exploratory web searches for "learning analytics curriculum" and "learning analytics [course|workshop|certificat e|program]" on Google (English, US) each returned several pages of relevant results. We then screened each result on the first ten pages of search results for relevance and focus on learning analytics, excluding programs that do not focus on learning analytics (e.g., programs about data analytics or about learning science). All relevant programs were added to the list. (2) Targeted web searches for programs at universities that house actively publishing learning analytics researchers, using Google and the university's search page, surfaced additional programs and events, which we screened for relevance and focus to include in the list. Once the list of programs was compiled using these two search methods, we reviewed all available official online materials for each program (information page, syllabus, timetable, admissions criteria, evaluation criteria, course materials, etc.) to categorise them by program type and record general program information (Table 8.1). The list of programs was widely shared on two community email lists (learning analytics and learning at scale) in September 2022 to solicit any additional programs omitted by our search process; this yielded an additional six programs that were added to the list. The scope of program characteristics is limited to surface-level information because the amount of openly available program information varies widely across programs. The final list of programs may not be exhaustive or internationally representative due to the nature of Google search in English and socio-cognitive biases of two US-based researchers. Nevertheless, the list provides the first formal overview of the characteristics of currently available—as of September 2022—learning analytics programs that are easily retrievable through English web search.

Table 8.1 Characteristics of current learning analytics programs organised by program type

Type	Level	Institution	Department	Title	Workload	Country
Degree	MPS	Carnegie Mellon University	Human-computer interaction institute; Department of psychology	Masters of educational technology and applied learning science (METALS)	2 years	USA
	MS	Columbia University teachers college	Graduate school of education, health, and psychology	Learning analytics	32 credits, 1 year	USA
	MA	New York University	School of Culture, education, and human development -learning analytics research network	Digital Media Design for Learning: Learning analytics and educational data science (LADS) specialization	36 credits, 2 years	USA
	EDD	Northcentral University	Education	Learning analytics in higher education	48 credits, 40. Months	USA
	MS	Stanford University	Graduate school of education	Education data science	51 credits, 2 years	USA
	MS	University of Texas Arlington	Department of psychology	Learning analytics	36 credits, 2.5 years	USA
	MS	University of Wisconsin–Madison	School of education, department of education psychology	Educational psychology—learning analytics	30 credits, 2 years part-time	USA
Certificate	Undergraduate and graduate	Algonquin College	School of education	Learning analytics	3 courses, 1 year	Canada
	Graduate	Brandeis University	School of continuing studies	Graduate certificate in learning analytics	5 courses	USA
	Graduate	Drexel University	School of education	Learning analytics certificate program	3 courses, 1 year	USA
	Graduate	Monash University	Faculty of information technology—centre for learning analytics	Graduate certificate of learning analytics	4 courses, 6 months	Australia
	Graduate	North Carolina State University	Online and distance education	Learning analytics	4 courses, 1–2 years	USA
	Graduate	University of Florida	College of education	Learning analytics	4 courses	USA
	Graduate	University of North Dakota	College of education and human development	Learning analytics certificate	4 courses, 1 year	USA
	Graduate	University of Technology Sydney	UTS open	Micro-credential on learning analytics	1 course, 6 weeks	Australia

Course	MOOC	Blackboard	Blackboard academy	Getting started with learning analytics	4 weeks, 20 h total	USA
	Undergraduate and graduate	Cornell University	Department of information science	Learning analytics	3 credits	USA
	Graduate	George Mason University	School of education	Perspectives on learning analytics	3 credits	USA
	Graduate	Georgetown University	Graduate school of arts and sciences—learning design & technology program	Learning analytics seminar	3 credits	USA
	Graduate	Harvard University	Graduate school of education	Multimodal learning analytics	4 credits	USA
	Graduate	Indiana University	School of education	Introduction to educational data sciences	3 credits	USA
	Graduate	KTH Royal Institute of Technology	School of electrical engineering and computer science	Introduction to learning analytics	7.5 credits	Sweden
	Graduate	Norwegian University of Science and Technology	Department of computer science	Learning technology and analytics	7.5 credits	Norway
	Graduate	University of Bergen	Department of information science and media studies	Introduction to learning analytics	7.5 credits	Norway
	Graduate	University of California Irvine	School of education	Learning analytics fundamentals	4 credits	USA
	Graduate	University of California Irvine	School of education	Learning analytics practicum	4 credits	USA
	Graduate	University of Eastern Finland	School of computing	Learning analytics	5 credits, 6 weeks	Finland
	Graduate	University of Massachusetts Amherst	Department of computer science	Educational data miningand learner analytics	3 credits	USA
	Graduate	University of Michigan	School of information	Learning analytics methods	3 credits	USA
	Graduate	University of Michigan	School of information	Learning analytics	1 credit	USA
	MOOC	University of Michigan	Via edX	Practical learning analytics	4 weeks, 2–8 h per week	USA
	Graduate	University of North Carolina at Chapel Hill	School of education	Learning analytics	3 credits	USA
	MOOC	University of Pennsylvania	Via edX	Big data and education	8 weeks, 6–12 h per week	USA
	Graduate	University of South Australia	UniSA education futures	Learning analytics and digital learning	4.5 credits	Australia
	MOOC	University of Texas Arlington	Via edX	Learning analytics fundamentals	4 weeks, 5–7 h per week	USA
	MOOC	–	Via canvas	Learning analytics and knowledge 2013	8 weeks, 5–10 h per week	International

(continued)

Table 8.1 (continued)

Type	Level	Institution	Department	Title	Workload	Country
Workshop	–	KTH Royal Institute of Technology	–	Nordic learning analytics summer institute	2 days	Sweden
	–	Learning analytics learning network	–	Learning Analytics Learning Network (LALN) event hub	–	International
	Graduate	Society of learning analytics research	–	Learning Analytics Summer Institute (LASI)	1 week	International
	–	Society of learning analytics research	International conference on learning analytics & knowledge	Building the learning analytics curriculum	0.5 days	International
	–	Society of learning analytics research	International conference on learning analytics & knowledge	Try R: A gentle intro to R for learning analytics	0.5 days	International
	–	University of Eastern Finland	School of computing	Learning analytics summer school	12 days	Finland
Resource	MOOC	Commonwealth of learning	–	Learning analytics: A primer	–	International
	–	New York University	School of culture, education, and human development -learning analytics research network	Learning analytics 101	–	USA

We observe that there are many different types of learning analytics programs that are offered, including self-paced open educational resource (OER) collections, conference workshops, massive open online courses (MOOCs), university courses, graduate certificates, and even entire master's degree programs. Most of the programs are offered by institutions that are highly ranked globally or nationally, and there is a skew towards programs offered by US universities that charge high tuition fees. However, several programs are international and broadly accessible, such as the OER or MOOC programs, though they do not provide formal university credit for completion. The majority of programs are offered by schools of education or related units, but some programs are offered by schools of information and computer science, or related units. The workload, even for programs of the same type, varies considerably in terms of the number of courses, credit hours, and time allotted for program completion.

This survey of the learning analytics education landscape highlights three major points. First, the field of learning analytics has gained maturity as indicated by high-profile institutions offering dedicated degree programs for learning analytics. More institutions around the world, and especially education schools eager to innovate, may consider this a signal to begin offering learning analytics programs as well. Second, the supply of learning analytics programs is remarkably tailored to diverse learner audiences from college students to graduate students to working professionals, which suggests demand for learning analytics training and credentialing from a broad range of interested parties. And third, the concentration of learning analytics programs in US universities and schools of education may limit global membership and state-of-the-art technology contributions, though there are a number of high-quality OER collections that can facilitate course offerings in more parts of the world and in more disciplinary areas going forward.

In reviewing the available online materials for each program, it quickly became apparent that there is no standard curriculum for learning analytics at this time. While most programs emphasised data literacy and an awareness of common analytic methods and systems as part of their learning goals, there was no common set of topics covered across all programs. Probably the clearest distinction between programs is in terms of how technical their curriculum and assignments are: for example, the seminar course at Georgetown University requires weekly response papers and a research proposal, while the lecture course at Cornell University requires weekly homework projects performing data cleaning and analysis in R. In 2021, SoLAR created an Education Working Group tasked with promoting "the development of high-quality Learning Analytics educational resources" (https://www.solaresearch.org/about/governance/solar-working-groups/). Initiatives from this group have included the development of a public learning analytics dissertation repository and a SoLAR In-Cooperation resource. This initiative invites submissions of any educational project that teaches learning analytics (including, but not limited to, courses, formal or informal programs, and textbooks) to be reviewed by the members of the working group who then provide feedback to ensure quality and consistency of the materials. After addressing the committee's feedback, the project receives an "In-Cooperation with SoLAR" certification, which can be publicly attached to the project to signal its coordination with the learning analytics community. The In-Cooperation project began in 2021 and, at the time of writing, supports the MS in Learning Analytics degree program from the University of Texas Arlington. This type of initiative can also provide guidance to institutions interested in developing new educational programs on learning analytics by recommending a curriculum.

8.3 Case Study: Learning Analytics at Cornell University

8.3.1 Course Overview

The *Learning Analytics* course at Cornell University has been offered in the Department of Information Science since 2018 by the first author. It enrols around 200 students affiliated with six different colleges and over 20 different academic majors on campus. Students are mostly undergraduates in their final years (juniors, seniors) and master's students in information or computer science, and a few doctoral students with an interest in education enrol each year. The course is designed to introduce students to various topics and methods in learning analytics and give them realistic opportunities to use education data to address practical issues and answer stakeholder questions. The course description summarises the motivation and goals of the course:

Technology has transformed how people teach and learn today. It also offers unprecedented insight into the mechanics of learning by collecting detailed interaction and performance data, such as in online courses and learning management systems like Canvas. At the intersection of education and data science, learning analytics are used to make sense of these data and use them to improve teaching and learning. This course blends learning theories and methodologies covering a wide range of topics with weekly hands-on activities and group projects using real-world educational datasets. You will learn how learning works, major theories in the learning sciences, and data science methods. Students collect and analyze their own learning trace data as part of the course.

Students are required to have foundational knowledge in programming and data analysis to enter the course because the course has a technical emphasis. However, the course does not assume any prior knowledge of educational or learning science theories. The official prerequisites state: This course is for undergraduate juniors, seniors, and graduate students interested in learning, education technology, educational data mining, and the broader implications of technology and data in education. Prior knowledge of probability and statistics (random variables, probability distributions, statistical tests, p values), data mining techniques (regression, clustering, prediction models), and fundamentals of programming is strongly recommended. Prior experience with the statistical programming language *R* is also recommended, as you will analyse data sets in *R* throughout this course.

The goal of the course is to prepare students for careers or further studies in education research, policy, and practice. By the end of the course, students are familiar with many foundational theories, contemporary trends, and widely used methods in the field of learning analytics and educational data mining. Moreover, they have gained experience working with raw, real-world datasets collected through education technologies, making informed decisions about how to clean the data, and interpreting the results of various methods that can be applied to the data to extract practical insights. Throughout the course, students consider the ethical, privacy, and equity implications of the applications they encounter to start forming a habit of considering these implications going forward. In line with these goals, the official learning objectives of the course are as follows:

- Explain key insights from learning science research and how learning works.
- Select and apply methods from educational data mining and learning analytics to analyse different kinds of educational data.
- Evaluate the results of different methods for different applications.
- Compare the strengths and weaknesses of methods for different applications.
- Identify potential benefits and risks of learning analytics for students, teachers, and institutions.

To accomplish these objectives, students complete readings, homework assignments, and group discussions on a weekly basis. The assignments are designed around authentic data extracted from educational technologies. For several assignments, students analyse data for their own class that is extracted from the course LMS. This makes the data and assigned questions to answer using the data especially personally relevant to students. The types of assignments are discussed in the next section and the strategy for incorporating learning analytics practice into the curriculum is discussed in the following section.

8.3.2 Course Structure

Students encounter a new topic in most weeks of the course. The lecture, readings, discussion section, and homework or group assignments during that week focus on the topic. What topics are included and how much time they receive represents a value judgment by the instructor. The topics can change over time as priorities shift and should be informed by an understanding of students' prior knowledge coming into the course and their career goals. The following topics are currently covered in the course: overview of what learning analytics is and why it matters; ethical and privacy considerations; how learning works; causal inference and A/B testing; multimedia learning and video analytics; assessments, psychometrics, and knowledge tracing; supervised and unsupervised predictive models; self-regulated learning; emotional learning analytics; learning analytics dashboards; and curriculum analytics.

In a typical week, students participate in the lecture which motivates the topic and the assignments for the week. They complete the readings and answer reading comprehension questions in the LMS to check their understanding, then they post a written summary on the discussion board and respond to another student's summary. The reading reflection posts and comments encourage students to identify and explain the core ideas from the week's readings, and compare their ideas to those of other students in the course. The specific reflection prompt in most weeks is "What are 3 things that you learned from the readings that you would tell someone who has not read them? Comment on someone else's reflection post to highlight an interesting takeaway that you had not previously thought of." Eager students who complete the reading reflection early tend to post longer and more thoughtful reflections, which are immediately visible to all other students and thereby establish a social norm to reflect deeply.

Students participate weekly in small-group discussion sections led by a teaching assistant to talk about the readings and homework assignment. The homework assignment for the week is either an individual or team mini-project that involves data analysis in most weeks. There are three mini-projects in this course that require students to work as a team and coordinate to solve a problem. Teams are formed at the beginning of the course and they persist for the duration of the course. This ensures that every student has a close group of peers who they can ask for help even if they are from an underrepresented major in the course. Persistent teams give students an opportunity to develop a group culture and collective intelligence to tackle more challenging mini-projects later in the course. Students are assigned into groups of five based on their chosen discussion section (students enrol in one of many sections to fit their schedule) and responses to questions on the required start-of-course survey. Teams are assigned within sections to especially balance prior experience with the R statistical programming language, such that all teams have a similar average level of prior experience.

The course follows a mastery learning approach with explicit learning goals for each week and many opportunities for feedback. Students' final grades aggregate lecture and section attendance (10%), reading comprehension checks (10%), reading reflection posts/comments (10%), homework assignments (55%), and group projects (15%). The first three components are intended to be formative and therefore given just enough weight for students to complete them. They are merely graded for completion to encourage continuous engagement with the course each week. Homework solutions are released 48 h after the due date. There are no midterm or final exams. The key to success in the course is to keep up with the material each week and ask for help early. Students can get help during weekly office hours and discussion sections, through the discussion forum, and from their peers.

8.3.3 *Course Content*

Overview of Learning Analytics
This introductory week introduces students to the field of learning analytics and educational data mining and gets them set up with the *R* programming environment that will be used for the homework assignments. Students watch a video from SoLAR (https://youtu.be/OOZhMjneMfo) and two introductory articles on big data in education (Baker & Inventado, 2014; Fischer et al., 2020). As a self-assessed homework, students load a dataset into *R* and generate a report with basic descriptive statistics using starter code posted online, including exploring the dataset and answering basic questions about it. The stated homework learning objectives are (1) Identify a dataset file format and use the appropriate function to load it, (2) Explore fundamental properties of a dataset using basic functions in R, (3) Compute and visualise relationships between variables using correlations, histograms, boxplots, and scatterplots, and (4) Calculate and visualise student- and question-level quantities and relationships.

Ethics and Privacy
The week on ethics and privacy engages students with questions about what data in education is collected by whom for what purpose, how the data is used, and what biases could emerge in the process. Students watch Neil Selwyn's keynote address at LAK 2018 (https://youtu.be/rsUx19_Vf0Q), followed by his article on *Re-imagining 'Learning Analytics'* (Selwyn, 2020). Students also read two complementary overview articles on algorithmic bias and fairness (Baker & Hawn, 2021; Kizilcec & Lee, 2022). The readings are discussed in sections and raise important questions for students, which the course returns to regularly. There is no homework assignment to provide extra time to get familiar with *R* and start reading for next week's group project.

How Learning Works
The week provides students an introduction to how learning works, based on learning science research, following a popular book on the topic Ambrose et al., 2010. Most students in the course have never taken an education course, thought systematically about how they learn and how learning works, let alone principles for effective teaching. All students read the introduction chapter and then, as their first group assignment, they create a 10-min recorded presentation as a team about one of the seven principles of how learning works covered in the book. Students upload and share their presentations with other students in the course and everyone watches one presentation for each of the seven principles. For this week's reading reflection, students post (and comment on) two concrete ways that they could apply principles in a gateway STEM course.

Causal Inference and A/B Testing

This week focuses on the value and process of causal inference using randomized experiments, or A/B testing, in education. Students learn about different ways of conducting random assignment and how to analyse data collected from a randomized experiment. Students read the first chapter from the *Book of Why* (Pearl & Mackenzie, 2020) and a review chapter of experiments in online courses (Kizilcec & Brooks, 2017). It is revealed that the prior week's materials had an experiment embedded where students either watched a TED talk about grit or read the transcript before answering the same set of ungraded questions about the talk. Deidentified data collected from this experiment is provided to students for their homework assignment. Students also learn how to create and analyse A/B tests. The stated homework learning objectives are: (1) Understand the difference between simple, complete, and block random assignment, and know how to implement them, (2) Check the balance of an experiment, (3) Analyse experimental data using a t-test, linear regression, and Wilcox test, and (4) Report results of an experiment.

Multimedia Learning and Video Analytics

The week covers multimedia learning theory, a cognitive theory of how people learn with different content and how content should therefore be designed, and video analytics, a method for analysing video activity data to gain actionable insights about learning and teaching. Students read chapters from *e-Learning and the Science of Instruction* (Clark & Mayer, 2011, chaps 2, 4), a handbook chapter on video analytics (Mirriahi & Vigentini, 2017), and a seminal video analytics paper (Guo et al., 2014). For the homework assignment, students analyse video analytics data from a MOOC lecture video, identify activity spikes and other notable watching patterns, interpret them by examining these event times in the video, and provide recommendations to the instructor for how the lecture video might be improved. The stated homework learning objectives are: (1) Explore the structure of video interaction data, (2) Identify parts of the video with increased activity, and (3) Decide what video analytics to report back to learners and instructors.

Assessments, Psychometrics, and Knowledge Tracing
The week covers knowledge and skills assessment, with an introduction to standardised test development and validation using psychometric methods (classical test theory, item response theory [IRT]), and Bayesian knowledge tracing (BKT). Students read a handbook chapter on measurement (Bergner, 2017) and an article about using IRT to analyse the force concept inventory (FCI), a widely used assessment in introductory physics classes (Wang & Bao, 2010). They watch an expert interview about BKT with Neil Heffernan, and optionally read a related (Pardos & Heffernan, 2010). For the homework assignment, students evaluate the psychometric properties of a standardised assessment, the FCI, that all students completed in the start-of-course survey. The stated homework learning objectives are: (1) Score and prepare an assessment for psychometric analysis, (2) Evaluate basic psychometric properties of an assessment like difficulty and reliability, (3) Apply and interpret an exploratory factor analysis, (4) Fit a Rash model and interpret Item Characteristics Curves.

Predictive Modeling: Supervised
The week on supervised predictive modeling covers a variety of uses and methods for predicting learner behavior and learning outcomes, with a focus on early warning systems. Students learn about different types of models to choose from depending on the prediction task and available data. Students read a commentary about not forgetting that learning analytics is about learning Gašević et al., 2015, a handbook chapter on predictive modeling (Brooks & Thompson, 2017), and watch a short talk about the bias-variance tradeoff in educational data science (Doroudi, 2020). The homework assignment is to engineer features from a math tutoring dataset (ASSISTments Math 2004–05 downloaded from DataShop; https://pslcdatashop.web.cmu.edu/) and fit several simple predictive models (linear/logistic regression, kNN, Naive Bayes, regression/classification trees, and random forest) to predict student dropout and the number of questions they eventually complete. Students compare model performance, iterate on features, and interpret their findings. The stated homework learning objectives are: (1) Understand how to identify a problem that can be encoded as a prediction task, (2) Identify appropriate outcome variables and predictor variables, (3) Create new features based on existing data, and (4) Build and evaluate several different prediction models. The homework prepares students for the predictive modeling group assignment that is due the following week. In teams, students build an early alert model for students in this course using de-identified LMS data (raw clickstream, assignment-level grades) collected up to this point. The goal is to predict who does not submit the most recent homework on time 24 h before the deadline. Students engineer features for different time periods to predict missed submissions each week only using data up to 24 h before that week's deadline. They compare different modeling approaches and choose the best performing one, incentivised by extra credit for the two teams with the highest f1 score. The team writes a reflection on their experience and reasons they would (not) recommend using the model in class.

Predictive Modeling: Unsupervised

The week on unsupervised predictive modeling has students learn about finding patterns in data using methods such as cluster analysis and dimensionality reduction, and how they are used for understanding how learning behaviors and performance differ across groups of students. Students watch video explanations of k-means and hierarchical clustering before reading two articles about clustering learners in MOOCs (Ferguson & Clow, 2015; Khalil & Ebner, 2017). As the predictive modeling group assignment is due this week, students only receive an ungraded activity that guides them through performing dimensionality reduction with principal component analysis (PCA) and k-means clustering. They use student activity data from the same ASSISTments dataset to find groups with similar engagement and performance in five steps: (1) Roll up the data to student-level variables to cluster, (2) Check correlations and reduce the dimensionality of the dataset with PCA, (4) Apply k-means clustering for different values of k, (5) Interpret the findings.

Self-Regulated Learning

The week covers self-regulated learning (SRL) theory, measurement, and interventions. Students learn about SRL phases and strategies, the use of self-report compared to clickstream data to detect SRL, and specific interventions focused on strategic plan-making and resource use. Students read a handbook chapter on learning analytics for SRL (Winne, 2017) and an article on strategic resource use interventions Chen et al., 2017, and watch a recorded interview with the study's lead author. The homework assignment has students search for evidence of established SRL strategies in the course's behavioural data and connect it to students' self-reported SRL strategies on the start-of-course survey (Kizilcec et al., 2017). Students propose ideas for features for each strategy, engineer them using the clickstream data, and examine how well they predict self-reported SRL strategies. This prompts students to realise the importance of instrumenting platforms to intentionally collect data about behaviors and processes like SRL. The stated homework learning objectives are: (1) Exploring response distributions of survey data, (2) Merging survey with behavioral data, (3) Engineering features that could represent SRL strategies, (4) Checking if any behavioural features predict survey responses using a linear model. Students also keep a diary of their own SRL activities for one of their classes to raise their SRL awareness.

Emotional Learning Analytics

The week focuses on emotions in learning, ways of measuring learner affect, and applications that use affect data to support teaching and learning. Students watch Sidney D'Mello's keynote address at LAK 2017 about multimodal analytics (https://youtu.be/3sZmWyhK690) and read his handbook chapter on emotional learning analytics (D'Mello, 2017), an article about clickstream-based affect detection Baker et al., 2012, and an article about gaze-based detection of mind wandering Hutt et al., 2017. The homework assignment has students build a boredom detector using another ASSISTments dataset with validated affect labels (downloaded from https://sites.google.com/site/assistmentsdata/). The state homework learning objectives are: (1) Engineer features that can detect affect in a dataset, (2) Train a Random Forest model to identify boredom and plot the model's ROC curve, and (3) Make recommendations to teachers based on the features that are important.

Learning Analytics Dashboards

The week covers ways of communicating learning analytics to different stakeholders, such as students and instructors, with visualizations and summary statistics using a dashboard. Students learn about characteristics of an effective dashboard and how to develop one from need finding to prototyping to implementation. Students read a handbook chapter on learning analytics dashboards (Klerkx et al., 2017) and articles about student-facing Bodily et al., 2018 and teacher-facing dashboards Echeverria et al., 2018). Students also watch a tutorial video for R Shiny (https://shiny.rstudio.com/) and ggplot2 (Wickham, 2016), which they use for their final group assignment: creating a student or an instructor dashboard for a Cornell course that has provided deidentified clicker data combined with student grades. Student teams have 2 weeks to plan what information would be valuable to present and how to present it, draw mock-ups and get feedback, implement the data processing, visualizations, and dashboard using R Shiny, and write a report reflecting on their design choices. The stated homework learning objectives are: (1) Understand the structure of clicker data, (2) Create multiple different visualizations, (3) Design and implement an instructor or student dashboard, and (4) Critically evaluate your own dashboard design.

Curriculum Analytics and Academic Pathways
The final week focuses on curriculum analytics and academic pathways in the context of undergraduate programs. Students learn about higher education data for course and major choices, course search, grades, and other attributes, and how they can be used to inform students, instructors, advising staff, and academic leaders. Students read an article about measuring and interpreting undergraduate course consideration patterns Chaturapruek et al., 2021, watch a talk on facilitating course articulation for transfer students by Zachary Pardos (Pardos et al., 2019), and on creating a lifelong learning marketplace by Mitchell Stevens (https://youtu.be/ehPs8qDs1V0). For the homework assignment, students analyse fully deidentified course enrolment records with grades. The stated homework learning objectives are: (1) Understand how course enrolment data is structured, (2) Identify hard course pairings using enrolment data, and (3) Identify course-major relationships to give students feedback about path dependencies.

8.3.4 Tools and Resources Used

The course uses edX Edge as the LMS because this makes it relatively easy to extract and provide LMS data to students. The edX data schema is less complex and requires less pre-processing to be usable by students compared to Canvas. A number of students have said that they appreciated the opportunity to try out a different LMS in this course: it gave them a better understanding of the nature of an LMS. edX Edge also facilitates the implementation of A/B testing and passing a hashed student identifier to a survey via the URL to conveniently connect survey responses to the behavioral data. Instead of the edX discussion board, the course uses Slack for general course updates and reminders, posting weekly reading responses and comments, and help-seeking in an asynchronous office hours channel. Each student team also creates a private channel for communicating amongst themselves. Students use direct messaging on Slack instead of email for any private or sensitive inquiries. To help students keep track of the weekly lecture, section, content release dates, and deadlines, a calendar file is created that includes all of these events and exported as a .ics file, which students can easily upload into their preferred calendar application.

The course readings and video presentations are either publicly available (e.g., SoLAR Handbook of Learning Analytics; https://www.solaresearch.org/publications/hla-17/) or accessible through institutional networks. The course uses the statistical programming language *R* with the graphical user interface RStudio (https://www.rstudio.com/), though it could also be taught in Python which the students are more familiar with, but many of them appreciate the opportunity to improve their ability to use *R* in this course. Most of the educational datasets are either publicly available, such as the ASSISTments dataset, or collected from students in the course using the edX LMS and the start-of-course survey. Other datasets are obtained from other courses or institutions, such as the in-class clicker or video analytics datasets. The number of publicly available datasets is increasing thanks to public competitions with educational datasets and efforts to promote open science practices that include releasing de-identified data (e.g., ASSISTments data repository https://sites.google.com/site/assistmentsdata/ and CMU DataShop https://pslcdatashop.web.cmu.edu/).

8.3.5 Incorporating Learning Analytics Practice Into the Course

Students benefit from the experience of working with authentic education data to answer personally relevant questions. In the words of one student in the end-of-course survey, "it felt like I was studying at the forefront of an emerging field and had a unique opportunity to participate and experiment with different ideas. I liked the freedom given to find solutions to problems." For many students, it is the first time that they think systematically about learning and teaching, the affordances of technology in this domain, and the opportunities and concerns that learning analytics bring. One student commented on this eye-opening experience, "I was introduced to a topic I had never even heard about. The psychological concepts presented throughout the course made me more aware of my own learning. It was also interesting to learn about the metrics (which I would have never thought of) that are used to assess and improve learning." Students who are interested in pursuing a career in data science are generally aware of opportunities in technology, financial services, medical, and marketing companies, but many of them are unaware of the options they have at education companies, as noted by another student: "The content of the course was really inspiring and made me think of data science in a completely different way. It inspired me to pursue a career and grad school education in learning analytics." A course on learning analytics can have a lasting impact on people's lives and lifelong learning practices by engaging them meta-cognitively with the process of learning and letting them discover what educational data is capable of and what its limitations are.

A recurring theme in the course is the cross-cutting consideration of ethics, equity, and culture. The weekly lecture and discussion highlight implications for student privacy, informed consent, data ownership, unintended consequences of well-intentioned interventions, questionable uses of student data, and randomized experiments in educational contexts to encourage students to think critically about how learning analytics affect people, institutions, and society. Students learn about current inequities in the education system and are encouraged throughout the course to attend to the ways that learning analytics applications might improve, perpetuate, or exacerbate them. Aside from algorithmic fairness considerations, the course lectures cover psychological theories (e.g., social identity and belonging, identity-based motivation, social norms, cognitive biases) that can help students understand how the users of learning analytics applications—students, teachers, staff, administrators—may act in ways that are not inclusive and potentially reinforce inequities. Finally, it is important for a course on learning analytics to acknowledge and reflect the diversity of cultural perspectives and practices for learning and teaching around the world. While the course content is US-centric, the lectures highlight examples from other cultures, and students who come from around the world are encouraged to share their educational experiences and contextualise the course content within their cultural frame of reference.

8.4 The Future of Learning Analytics Education

Learning analytics education today is highly distributed—geographically, methodologically, and across disciplines. This is a promising indicator of the growing popularity and strong value proposition of learning analytics to a variety of stakeholders beyond academia. It is important that the community maintains a balance of upholding its core principles while simultaneously expanding to accommodate and reap the benefits of a growing list of partner disciplines. Success in this regard will largely stem from the manner with which future generations of learning analytics researchers and practitioners are trained. We are at an important crossroads now as we come to terms with this fact: *none of the current leaders in the learning analytics field were trained as learning analysts*. The term "learning analytics" simply did not exist, and neither did learning analytics curricula. Each leader was drawn to the unprecedented troves of educational data made possible by the advent of large-scale open online learning, carrying with them their disciplinary practices along with shared passions and curiosities for the science of learning. While it only takes a small group of visionaries to invent a discipline, it takes a highly coordinated community to grow and nurture one.

From reviewing and comparing the programs identified in our survey of the landscape and closely examining the curriculum of a specific course, we distilled the following takeaways and recommendations for the community to reference when designing and building learning analytics courses. We do not intend to build walls around rigid guidelines defining the discipline, but rather to encourage current and future educators and learners to consider promising approaches and innovations in this domain.

- *Build a theoretical foundation*—Before students are asked to conduct any analyses or learn a new programming language for data processing, it is critical that they first develop a strong foundational understanding of the field from its inception to the state of the art. This enables students to properly justify and contextualise their own analyses by intentionally selecting the types of problems, questions, and methods they engage with. It encourages students to be critical consumers and informed producers of learning analytics insights. Developing this theoretical foundation will help students achieve a new literacy for peer-reviewed quantitative research articles that can allow them to stay up-to-date in a fast-moving field. Which specific theories should be taught as part of this foundation varies across programs for now but may converge into a theoretical core in the future.

- *Include practical quantitative elements*—Courses should be designed such that students have at least some hands-on experience with educational data. Ideally, this would also entail using a programming language such as R or Python (instructors should select whichever language fits the context of the program), but spreadsheet-based tools like Microsoft Excel are also useful for conveying the same core ideas. Students benefit from learning and honing the skills of using a programming language to conduct their own analyses, however simple they may be, because they learn about all of the decisions that go into any such analysis. This provides them with the awareness, literacy, and understanding to evaluate learning analytics findings and the methods used to arrive at them.
- *Make learning analytics self-relevant*—Learning analytics courses can draw students from a wide variety of backgrounds, as reflected in the diversity of departments that offer them. Instructors should embrace this diversity by encouraging students to bring their own interests and experience to the table. For example, when students work on analytical (research) projects during a course, it can be a meaningful experience if they have the option to bring their own dataset—whether it is one from their primary job, volunteering, or one found online—or the possibility to analyse their own individual and classroom-level data, as illustrated in the case study.
- *Encourage critical reflection*—Learning analytics courses may be the first time students learn about all of the data generated from their interactions and performance, how these data might be used in practice, and potential randomized experiments embedded in their courses. This can lead students to raise concerns over privacy, ethics, and regulations. These concerns should not only be addressed but welcomed and openly discussed in the course. For learning analytics to continue developing as a field, instructors and researchers need to have an ear to the ground and understand students' concerns and how they make sense of them. Not only will it help address the concerns, but it can also inform future research and product development.
- *Open-source course materials*—To advance our collective understanding of learning analytics education, we encourage instructors to make their syllabi and resources available online whenever possible. Not only does this increase the reach and accessibility of learning analytics materials to broader audiences, but it also fosters a sense of community among instructors who can learn from and build off of one another's teaching approaches. Instructors can further participate in opportunities to exchange ideas and materials about teaching learning analytics at conferences or other social convenings.

A relatively nascent field, learning analytics benefits from the flexibility to respond to emerging issues in education and digital technology. When ethical concerns around big data and technology firms gained traction in the public sphere, the learning analytics community swiftly began devising frameworks and publishing research about the role of ethics and privacy in the collection and use of educational data (Slade & Prinsloo, 2013). This has also encouraged efforts to prioritise teaching a code of ethics in learning analytics courses (Prinsloo & Slade, 2017). Moreover, in response to the 2020 racial justice movement to address systemic issues of justice, equity, diversity, and inclusion, the learning analytics community committed to "identify and eliminate racial disparities…[and] mobilise our expertise and connections with communities to actively contribute to the hard work of promoting social justice and dismantling injustices in education" (https://www.solaresearch.org/2020/06/statement-of-support-and-call-for-action/). Learning analytics educators can contribute to this cause by exploring ways to teach learning analytics to empower students to eliminate disparities and promote social justice. Finally, learning analytics applications are increasingly adopted in parts of the world with cultural norms and values about teaching and learning that differ from those in Western nations, including differences in epistemological beliefs, pedagogical orientation, uncertainty tolerance, and methods for consensus building (Kizilcec & Cohen, 2017; Baker et al., 2019; Rizvi et al., 2022). Including different cultural perspectives in the learning analytics community is essential to building an inclusive body of knowledge and avoiding imposing Western educational values in other contexts. Educators have the power and arguably a responsibility to show this diversity of thought and practice to their students by not only selecting readings, case studies, datasets, and class projects that are culturally relevant but also ones that expose them to unfamiliar cultures. Given the preponderance of learning analytics education programs from Western countries we observe in our review, there is a need to intentionally check that our community is promoting teaching and learning of learning analytics in a culturally inclusive manner. We hope that the insights and guidance provided in this chapter can facilitate the development of new educational programs around the globe.

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Chapter 9
Learnersourcing Analytics

Richard Glassey and Olle Bälter

9.1 Introduction

Learnersourcing can be succinctly defined as crowdsourcing from students in a learning context (Kim, 2015; Jiang et al., 2018). Crowdsourcing emerged as a concept from the Web 2.0 era when new Web technologies combined with increased Internet access, online participation, confidence and trust facilitated a rebalancing between information producers and consumers and led to the explosion of user generated content (Howe et al., 2006; Brabham, 2013; Krumm et al., 2008). The same basic factors have also helped to facilitate the growth of learnersourcing in education (Jiang et al., 2018), along with the emergence of specific learning platforms that promote learner participation in content production (Denny et al., 2008; Khosravi et al., 2020), as well as the pedagogical motivation to do so is better understood and teachers can feel comfortable in sharing the task with students (Doroudi et al., 2018). With crowdsourcing the economy of scale allows a large amount of content to be generated with little production cost as it is distributed over so many users (Brabham, 2013). However, there is no guarantee of consistent quality across that content; rather the opposite, a small amount of content might be of high value, whilst the remaining long tail may be of little or no value (Allahbakhsh et al., 2013). Furthermore, simply having more content means that there are new management challenges which go far beyond what individuals can manage and depend more upon automation, analytics and artificial intelligence (Kamar et al., 2012).

The same challenges apply with learnersourcing – it can greatly help with solving the scale issue by having students engage with production, however the issues of quality control, incentivisation and management emerge (Khosravi et al., 2021).

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Not all students will produce content reaching the desired level of quality that makes it useful for other students' learning (some content may be detrimental if it adds confusion or propagates misconceptions); not all students will be equally motivated to generate content leading to a participation inequity that requires a balance between voluntary, incentives and mandatory strategies; and finally, this is a new area that requires support for teachers to make sense of learnersourced content within their courses which requires a shift in perspective as well as new forms of automated support as part of smarter learning environments.

In this context, there is an opportunity for learning analytics (Viberg et al., 2018) to play a vital part of the solution (Khosravi et al., 2021). This chapter will provide a background on the emergence of learnersourcing as a topic, a taxonomy of the types of learnersourcing data and their supporting systems that increasingly make learnersourcing practicable for learning analytics, and concludes with a summary of the challenges.

9.2 Background

Learnersourcing was coined as a term in 2013 in two CHI Extended Abstracts (Kim et al., 2013; Kim, 2013). It meant that learner activities within a system could be leveraged to provide useful input. The inspiration came directly from the example of how computer vision problems, like image classification, could be complemented with crowdsourced input from users, such as manually annotated training data that algorithms could learn from (Kovashka et al., 2016). Whilst this initial use of learnersourcing focused on using students to annotate regions of video content, since then many other examples have emerged – a literature survey of "crowdsourcing for education (CfE)" identified 51 independent learnersourcing initiatives (Jiang et al., 2018).

However, learnersourcing does not mark the beginning of leveraging student activities in such a way to increase the overall quality of the learning environment – any single student contribution to teaching that has benefit for other students falls into the definition given at the start of the chapter. Students posting questions on public forums where teachers, teaching assistants or other students can all collaborate to improve the learning environment by answering questions collectively is one such example that has been possible ever since mailing lists and other bulletin board systems became integrated into the digital teaching environment (Wild, 1999; Weisskirch & Milburn, 2003). Students creating collaborative lecture notes via a wiki interface that allows multiple authors, editors and commenters to collectively produce a higher quality result than a single student might manage alone (O'Neill, 2005; Parker & Chao, 2007). Students reviewing each others' assignments as part of an online peer-review process can also be seen as a means of distributing the effort in order to increase the amount and timeliness of feedback students might otherwise receive (DiGiovanni & Nagaswami, 2001; Sharma & Potey, 2018). Thus, it is somewhat challenging to draw a specific line in the sand where collective activity and learnersourcing are substantially different.

In their doctoral thesis on learnersourcing, Kim divides the concept into passive and active learnersourcing (Kim, 2015). Passive refers to natural learner interactions that if gathered could lead to positive changes in the learner environment (Doroudi et al., 2018; Kim, 2015). For example, in a traditional lecture theatre a teacher can react in real-time to give further explanation where there is confusion (and hopefully remember that for the next time), whilst with a pre-recorded video lecture, there is no such opportunity. However, if a system can observe how students interact with this content, perhaps pausing, rewinding and re-watching particular segments to the extent that a pattern emerges, then this is data that can be used to improve that segment; in the short term an annotation could be rerecorded if it was deemed confusing based on the amount of annotation generated.

Active learnersourcing on the other hand requires that the student actively contribute something to improve the learning environment (Doroudi et al., 2018; Kim, 2015). Continuing with the theme of the video lecture and a segment of confusion as our example, students could contribute both questions (e.g. what do they mean here by 'linear cost'?) and explanations (e.g. 'linear cost' here means that to solve the problem we must consider all elements in a given collection) as annotations to the original content. Here we find a step change in interaction – students are now themselves authors of content, or at least part of it. In both cases of active and passive learnersourcing, the goal is to collectively and iteratively improve the learning environment by leveraging this content.

Irrespective of active or passive, both forms of learnersourcing produce data and systems that support learner sourcing can expose this data to further analysis (Doroudi et al., 2018). Learning analytics therefore has much to gain from the development and design of learnersourcing systems to make both active and passive data available (Khosravi et al., 2021). Already, the active and passive interactions that students have with learning platforms, such as official learning management system (LMS) (e.g. Canvas or Moodle) or unofficial platforms that host content (e.g. YouTube) provide click data, engagement data and dwell time data that feed into learning analytics (Black et al., 2008; Park et al., 2016). The next section will map out a taxonomy of the different types of learnersourcing activities and the data they produce that have so far been published in the literature as well the learning analytics potential on the value of this type of data.

9.3 Taxonomy of Learnersourcing Data

As established, learnersourcing is still in its infancy. Despite this, there have been a wide range of developments in this area to the extent that clear boundaries are starting to emerge between the different types of learnersourcing platforms, what they primarily aim to achieve and ultimately what types of educational data are generated (Jiang et al., 2018). Previously, a short article proposed a taxonomy of learnersourcing in terms of source (who creates content), pedagogical content knowledge required, effort and task complexity, domain knowledge required, and the amount of structure required (Mitros & Kim, 2015). Here, rather focus on the learner, we focus specifically on the data that is generated with respect to practicable application to learning analytics, with the aim of giving focus to learnersourcing data. In the following sections aspects of learnersourcing activity: content annotation, resource recommendation, explanations of misconceptions, content creation, and evaluation, reflection and regulation will be described using examples from the literature.

9.3.1 Content Annotation

The first activity aims to improve existing learning material, or content that has already been produced, most likely by an expert, such as a teacher. Whilst the content provides the main value, the value-added content coming from annotations should further enhance this value (Zervas & Sampson, 2014). A simple example is a long form video of a lecture. Given a platform that supports annotations, one or more students can add timestamps to help other students jump to the most relevant section. This "chaptering" or signposting activity enhances the original content, saves time for the teacher, who does not have to go through the laborious tasks of both producing content then annotate it, and saves time for the many students who want to navigate directly to a specific topic without having to trawl through an entire lecture; essentially a win-win situation (Kim et al., 2013). Taking this to the extreme, students can be recruited to collectively caption entire video lectures (Zhang, 2021), illustrating the collective power to make large problems small. The following examples and findings of content annotation can be found in the learnersourcing literature.

Given the explosion in the use of video in helping to make learning content more accessible and available to ever more learners, it is here where some of the earliest works in learnersourcing emerge (Kim et al., 2013). Sub-goal labelling is the technique of helping learners to build better mental models by making a hierarchical structure of steps and clustering them into sub-goals, which then helps learners to adjust to new problems that are related (Catrambone, 1998). One can think of a recipe for a meal as made up of sub-goals that, once executed, will help in future related meals (e.g. the sub-goal of preparing rice). In the context of video content, many videos fall into a how-to format – 'explainers' that walk learners through a series of steps that inform towards a new understanding or corrects prior misconceptions (Muller et al., 2008; Margulieux et al., 2012). Despite the popularity of this content, learners still struggle as there may be no index of steps, nor any hierarchical structure due to the linear nature of the format. In fact, as learners engage with this content they are actively analysing and inferring mental models, so it would be beneficial to channel the collective effort into providing annotations as a form of sub-goal labelling to improve its quality (Juho Kim et al., 2013).

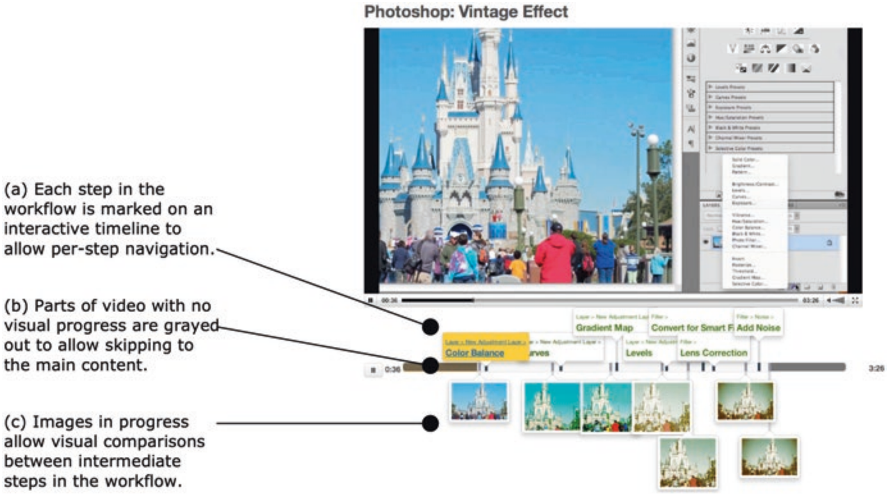

Fig. 9.1 Toolscape user interface for leanersourcing student generated sub-goal annotations for Photoshop tutorial videos. (Adapted from Kim, 2013)

ToolScape (Kim, 2013), as shown in Fig. 9.1, was developed to support this form of learnersourcing, where Photoshop video tutorials were annotated by learners. By engaging the learners with quizzes and opportunities to label whilst engaging with videos, ToolScape could amass large amounts of possible annotations which then assist AI methods in determining how to provide future learners with high quality annotations and better navigation structure through the content. This form of sub-goal annotation via learnersourcing has also been successfully applied to the very different contexts of solving math problems in the SolveDeep system (Jin et al., 2019), learning foreign languages in the Exprgram system (Jo et al., 2017) and classifying and interlinking Islamic texts (Basharat, 2016).

Once again, the motivation for this approach is clear, students benefit when learning material has been annotated and given structure (Margulieux et al., 2012), however the cost to content producers is prohibitive to provide high quality sub-goal labelling (Kim, 2015). Taking a learning analytics perspective, how the learners engage with this type of activity and the variance in their suggestions of appropriate annotations creates an interesting data set to study on top of their regular interaction with learning content. In this case, participation is perhaps not such a large issue for solving with learning analytics – only a few sets of quality annotations are required to benefit a large number of students. Rather the relevant use for learning analytics is to ensure that content does find its way to being annotated, perhaps by systems both identifying gaps automatically and then recommending them to students as areas where their activities can help other students.

However, as with crowdsourcing, without incentives or mandatory structures around content annotation, it could fall to the same students that just like the activity, rather than be more evenly distributed. So, whilst many alternative annotations may not be needed, ensuring that new content that emerges throughout a course is annotated by those who have previously not conducted the activity might be advantageous. Automating this through learning analytics makes sense as the management effort for teachers would become challenging to keep track. Rather, a participation dashboard might help to expose how much content has been annotated and which students have (or not) participated. Whilst such learnersourcing systems for content annotation are still very much research projects and not widely adopted or adapted into common LMSs, the positive results gathered so far on engaging students and improving content with little or no cost to producers suggest their adoption will grow, however appropriate use of learning analytics will be a critical part of the success of their acceptance.

9.3.2 Resource Recommendation

The second activity aims to go beyond the official internally produced content that may be offered in a course and instead integrate unofficial content that has been produced externally. Rather than enhance the existing content, the idea is to open the course up to include content that students find elsewhere that they deem to be useful and relevant (Jiang et al., 2018). In business and management, "Not Invented Here (NIH)" syndrome describes the situation when a company feels compelled to create their own solution in-house, even when a superior external solution already exists (Antons & Piller, 2015). The same observation can be applied to the education sector, where teachers repeatedly solve the problem of creating course content rather than reuse what material may already exist (Atkins et al., 2007). However, students now have instant access to open educational material, both formally produced by teachers and informally produced by amateurs, and shared online with open access (Wiley et al., 2014). Students may also be motivated to find such material if the official course content is dated or difficult to follow, or provides insufficient coverage of a topic (Zlatkin-Troitschanskaia et al., 2021). By enabling students to discover, rate and curate this external material officially within a course, then the benefits are shared with all students who may not be motivated to look themselves or simply trust that their teacher has already saved them the effort with the official content (Li & Mitros, 2015). Depending on the topic, there can be a deluge of treatments in different formats, and having students distribute this effort allows for the most relevant, recent and valuable material to be considered content for the course. The following examples and findings of resource recommendation can be found in the learnersourcing literature.

Li and Mitros (ibid.) recruited students to provide recommendations for resources that would help remedy student misconceptions during a quiz. As Fig. 9.2 shows, students taking an online problem set in an introductory programming course are presented with a "Related Resources" box underneath the problem they are currently trying to solve. Rather than be provided by the teacher, this box displays the curated resources that other students have felt relevant to solving this problem. The

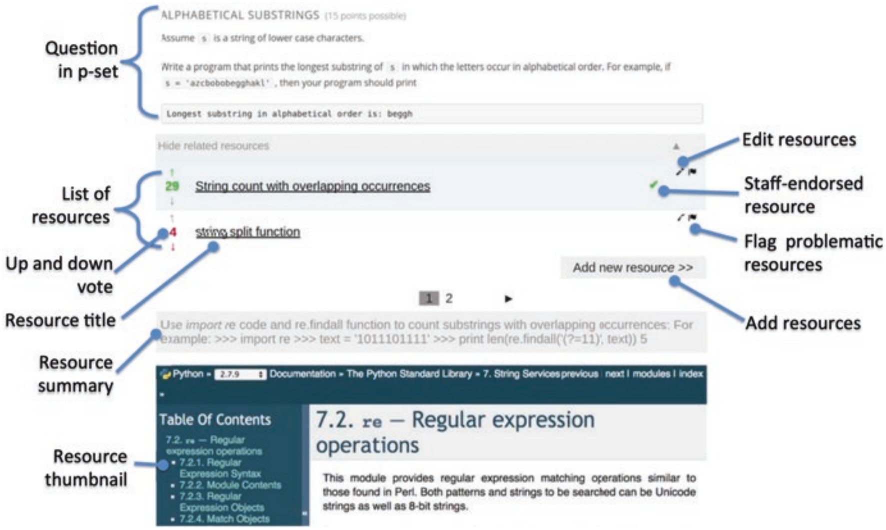

Fig. 9.2 Recommendation remediation user interface that both learnersources resource recommendations for a given problem set, as well as moderations on those resources to ensure the best is the most apparent to future students attempting the problem set. (Adapted from Li & Mitros, 2015)

interface allows students to add resources as a hyperlink, describe them, vote them up or down, flag problematic resources, as well as see resources that have been suggested officially by teaching staff of the course. Finally recommended resources are previewed graphically via a slider interface that lets students quickly navigate through and select a resource.

The form of data captured is principally aimed toward websites that might be useful to solving the problem, but not being too specific (Li & Mitros, 2015). However, this learner activity also engages students in the quality control aspect of resources; with content moderation features as well as flagging resources for teaching staff to review in case of inappropriate content or content that simply solves the problem directly. In terms of learning analytics, this gives the possibility to identify questions that may be too challenging given the resources that are recommended, or determine which questions generate the most activity through the content moderation data. Despite this being a single question from a problem set, a new layer of rich learner data can be extracted.

As this is a collective voting activity, it is expected that inferior or inappropriate content will simply sink down recommendation lists whilst higher quality content raises higher up. Thus, both quality and management concerns are naturally solved as part of student recommendation and moderation behaviour. However, it can be expected that not all students participate actively in this behaviour, however in this case it is difficult to see any major concern that would have to be addressed with a learning analytics approach; that said, this form of contribution to course content is clearly meriting and keeping track of participation may be viable using a dashboard to identify the over and under achievers.

In another use case, the most relevant resource might not be the most desirable aspect to use learnersourcing towards. In Lightfoot (2012), the social bookmarking service "del.icio.us" was used in a politics course to keep up with the pace of relevant news articles regarding EU governance. Here, given the "nature of politics as a discipline is that it is constantly evolving such that new developments and policies emerge almost every day. It is therefore imperative that the students keep on top of these developments and crucially engage with them in a critical manner" (ibid.). Students in the course were tasked with creating reading lists to compliment the course and organise these using the social bookmarking service, that allows both axes of chronology and quality to be captured via the ordering and voting features provided by the interface.

However, despite the wide variety of different types of content that were curated, active participation by students was reported as only amounting to 5% of the students, which reflects the general trend observed in crowdsourcing of participation inequality, sometimes referred as the "90-9-1" rule (90% observe, but don't contribute; 9% contribute only occasionally; and 1% contribute most actively) (Allahbakhsh et al., 2013). Beyond this the authors reported the threat to provision of service, as the social bookmarking service was already in the process of being sold and is by no longer in service.

This valuable data enriched the course beyond what would have been possible for a single teacher to curate disappears with the service. Future between course comparisons is now more difficult to make even if alternative services are found. Much of the progress in learning analytics is data-driven and ease of access underpins this. Learnersourcing approaches are not yet fully integrated into mainstream learning management systems and in order for learning analytics of learnersourcing activities to flourish, data must be curated in ways that are accessible and persistent, much like engagement data and assessment results are preserved in current LMSs.

9.3.3 Explanations of Misconceptions

The third activity aims to go deeper in terms of adding value to existing content or sourcing new related content by having students attempt to provide explanations of misconceptions. There is a clear shift from administrative and organisational contributions towards having students help other students understand concepts. Essentially students can be promoted to teacher in order to resolve a misunderstanding that one or more students may have. An example here is the Perusal learning platform (Miller et al., 2018) that is designed to support students' collective engagement with reading material in a course, as shown in Fig. 9.3.

Students can be assigned a reading task, and the system allows students to highlight regions of text that they have some misconception about and these regions can spawn discussion threads where multiple students can contribute their own

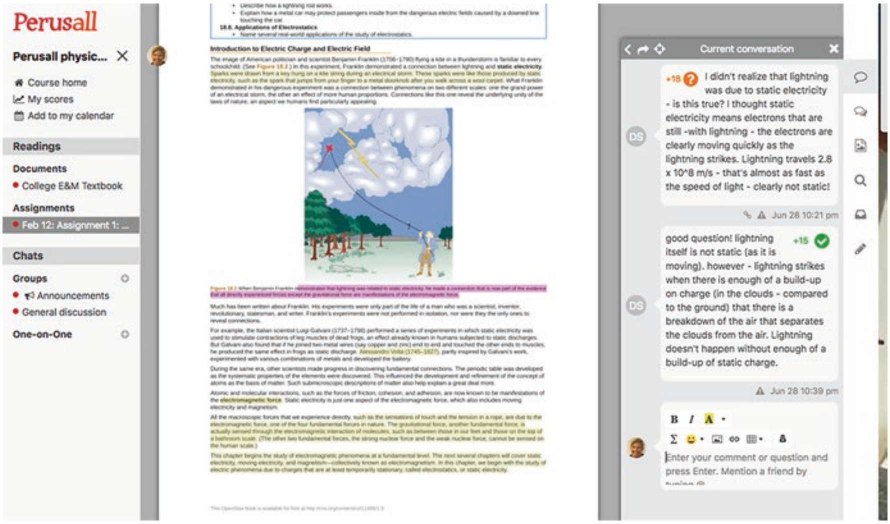

Fig. 9.3 Perusal user interface for collaborative reading. Groups of students can be assigned a reading task and their questions, explanations of misconceptions and discussions are made visible to the rest of the group as well as the teacher. (Adapted from Miller et al., 2018)

interpretation and opinion. The platform allows teachers to create small reading groups of students such that the interaction is localised and this very much becomes part of the reading exercises – students in their groups can be tasked to read the text, ask questions and engage in discussions, taking the solitary task of reading and making it more open to collaboration and including awareness of how your peers are engaging and receiving it, whilst letting teachers clearly see where students engage the most in terms of questions, explanations and discussion. The following examples and findings of content annotation can be found in the learnersourcing literature.

It has been long understood that the best situation for learning is when a student has direct one-to-one access to a teacher who can give dedicated real-time feedback to correct misconceptions (Bloom, 1984). Yet the economics of this situation are also quite unrealistic and much research has been targeted at finding ways to personalise learning in the face of the inequality between many learners and few teachers (e.g. advances in online education, MOOCs, artificial intelligence and personalisation (Yu et al., 2017).

Glassman et al. (2016) leveraged learnersourcing to provide personalized hints in design tasks in engineering. Two systems were developed, “Dear Beta” (shown in Fig. 9.4 and “Dear Gamma”, to gather hints and tips from students in order to help other students who are struggling with a task. The main insight was that through student’s own personal struggle (and its resolution) they became experts in helping others resolve similar struggles. By capturing these hints and tips, the system can present them to students in the future. Furthermore, students can vote on hints in order to promote the most useful and demote the unhelpful ones.

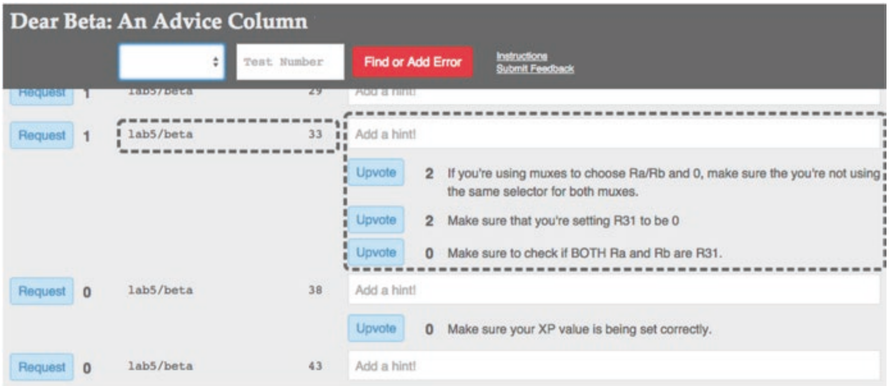

Fig. 9.4 Dear Beta user interface for learnersourcing hints and tips from students in order to help other students who are attempting the particular task. (Adapted from Glassman et al., 2016)

However, voting still offloads the effort of finding quality in student generated hints and tips. Williams et al. (2016) used learnersourcing to elicit explanations to math problems with the addition of machine learning to help differentiate between those which are most helpful to students or not. This combination was found to be surprisingly satisfactory for the teacher involved in the study who stated that the top-rated explanations as judged by machine learning were comparable to their own explanations for the same problem.

Once again, the learning analytics perspective here is that whilst one can generate hints, tips and explanations at scale to overcome the inequality between students and teachers in terms of numbers, the matter of quality management becomes an even bigger problem leading to the rhetorical question – what benefit is an explanation if it is a bad one? Increasingly, the combination of learnersourcing, machine learning and human-in-the-loop AI are pointing towards solutions towards this more general question of how to manage the quality of what is generated whilst making it convenient for teachers (Khosravi et al., 2021; Williams et al., 2016), which will be further discussed in Sect. 9.3.5.

9.3.4 Content Creation

The fourth activity represents a significant shift in what is expected of students; they become the authors of original content that will be used by other students when learning about a topic. Given the time and effort that teachers invest in their content, this form of learnersourcing represents a high risk / reward proposition – the reward is reducing the time and effort that goes into producing content at scale for the teacher; and the risk is the loss of control of quality over the content produced as well as a new task of who to manage all the newly produced content. In terms of the

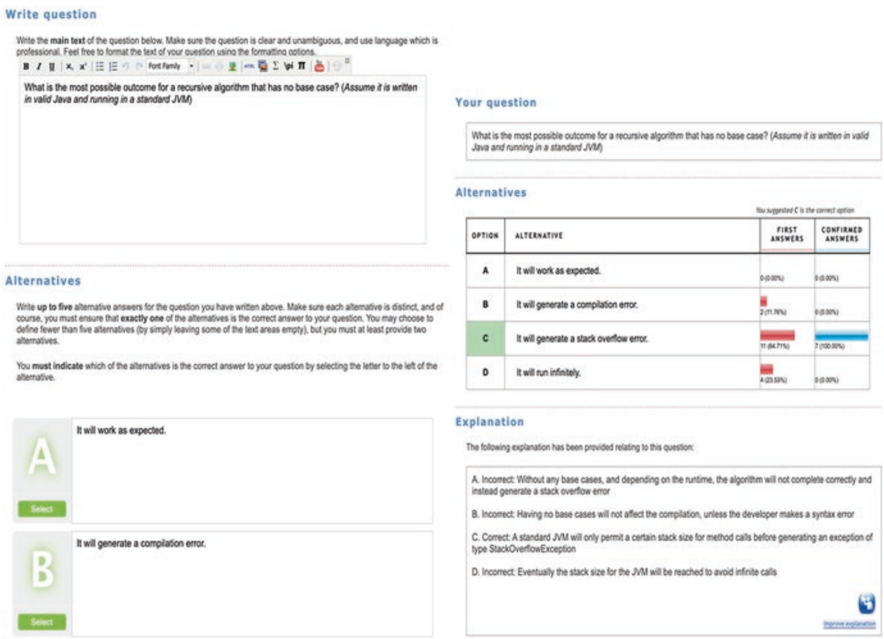

Fig. 9.5 User interface for PeerWise. The left-hand image shows the interface that students use to create multiple choice questions. The right-hand image shows the interface for presenting the answer and explanation to students

learnersourcing literature, two systems have come to dominate the space – PeerWise and RiPPLE.

The popular[1] PeerWise platform allows students to create multiple choice questions themselves as well as answer questions produced by other students (Denny et al., 2008). Figure 9.5 shows both interfaces for creating and answering questions. The platform is dedicated to these two activities and as long as students engage with both, there is no requirement for a teacher to do anything other than enrol students. In terms of scale there are no real limits – students can produce and consume questions indefinitely. In terms of quality the platform provides feedback and ratings in order to help improve existing questions, also allowing students to disagree with the answer in case of production mistakes. Despite the opportunities of this form of learnersourcing, the challenges of managing both the scale and quality demands attention and planning on the part of teachers using this type of platform, not to mention the question of participation and recognition of this additional labour impressed upon already busy students.

In terms of data, despite only targeting one activity of creating questions, PeerWise exports data about the questions, who created them, how they are labelled,

[1] According to the PeerWise homepage (https://peerwise.cs.auckland.ac.nz/ over 2500 institutions have registered to use the system).

how many correct and incorrect attempts have been made, the history of edits, the comments given as feedback to the creator from their peers as well as the quantitative scores of quality and difficulty. Whilst there is no standard format for learnersourced data, the creators of PeerWise have made it easy to export to common CSV and spreadsheet formats so that the data can be further analysed beyond the analytics built into the user interface itself.

In terms of learning analytics this gives a rich picture into two sides of creation and consumption of a learning activity. This insight could be very interesting for learning analytics in general as the process of generating learning content has been often considered to activate deeper learning for students. As any teacher knows, a significant amount of effort goes into creating educational content, and it is hard to imagine how having students generate questions in PeerWise would not activate deeper thinking, learning and reflection amongst students. But there have been precious few attempts to actually measure this in any objective manner, which of course would be the ideal place for learning analytics to make a contribution.

In terms of impact, PeerWise has an impressive academic record. At least in the academic literature a query of "PeerWise System" yields 230 results via Google Scholar and removing the keyword 'system' yields 1130 results. Despite this, the system is limited to multiple choice questions and even then, there is not much flexibility (e.g. you can have a maximum of five alternatives and only one explanation for the question irrespective of a correct or incorrect attempt. However, it undoubtedly paved the way for the next content creation focused system. If PeerWise could be consider "Web 1.0", then RiPPLE can be considered the "Web 2.0" of learnersourcing.

RiPPLE is described as a "learning tool that help you provide an, active, social and personalised learning experience, at scale" (Khosravi et al., 2019; Khosravi et al., 2020). The first major difference from Peer-Wise is that it supports the creation of multiple activities, not just multiple choice questions (see Fig. 9.6 for a list of activities that can be learnersourced).

The second major difference is that instead of just creating a bank of activities, RiPPLE acts more like a complete learning management system that allows a course designer to both add their own content, but also create a skeleton structure of topics that require activities to be created by students. The third major difference is that the system determines the mastery of the student and attempts to recommend activities that have the best chance of taking them forward, rather than wasting time on activities they already have the requisite skills for (Khosravi et al., 2020). Students also get to see a learning dashboard where they can see how they stand within their own subjects and how they compare to their peers in aggregate (see Fig. 9.7).

In many ways, RiPPLE is a system that is already active within the intersection of learnersourcing and learning analytics, blending the best ideas from both fields into a system that benefits students and teachers alike. Whilst PeerWise has existed longer and penetrated further into the academic world, RiPPLE appears to provide a step forward in the ambition of what a learnersourcing system with practicable learning analytics should look and be like.

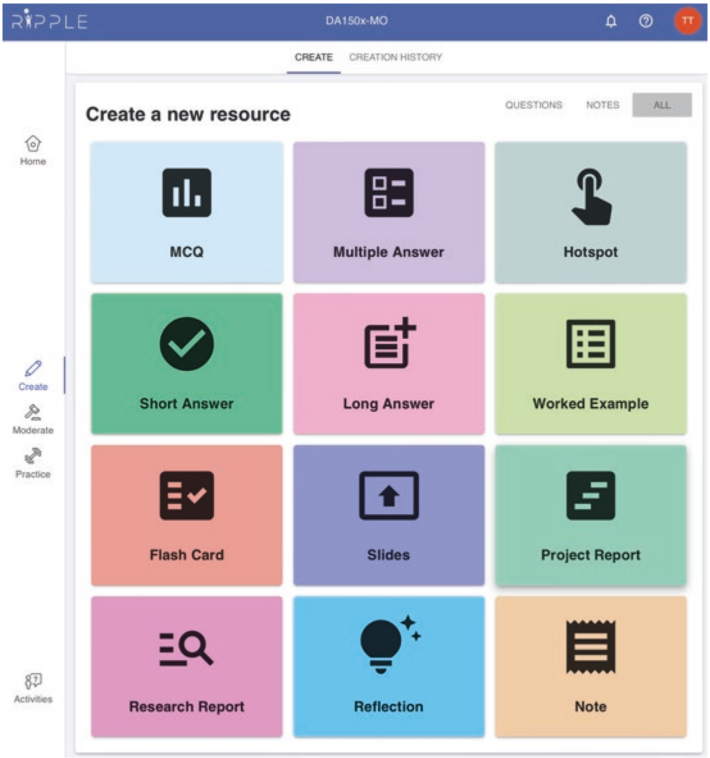

Fig. 9.6 RiPPLE user interface. When a student using RiPPLE selects the create button, they are presented with the following choices of learnersourcing activities they want to create

The first part of this is the data-driven approach that RiPPLE has adopted to addressing the issues of quality, participation and management. The creators included content moderation in the early versions of the system, no doubt influenced by what can be seen in the PeerWise system for content moderation Fig. 9.8. However, as reported in Khosravi et al. (2020) they have also used the data gathered, student engagement and feedback to refine the interface into a more effective means to capture quality evaluations Fig. 9.9. Furthermore, a more refined model of the content moderators also helps to clearly identify the trustworthy and useful reviews over those who put the least effort and attention into the moderation activity (Darvishi et al., 2021).

For the second part, student participation, data on use of RiPPLE with student populations in an open and voluntary modes during courses closely mirrored the 90-9-1 participation ratio found in other examples of crowdsourcing, as discussed earlier in Sect. 9.3.2 and in more detail in Allahbakhsh et al. (2013). To improve on this situation, mandatory participation that bears credit is the most obvious step to remedy the participation problem, but there are also efforts to incorporate

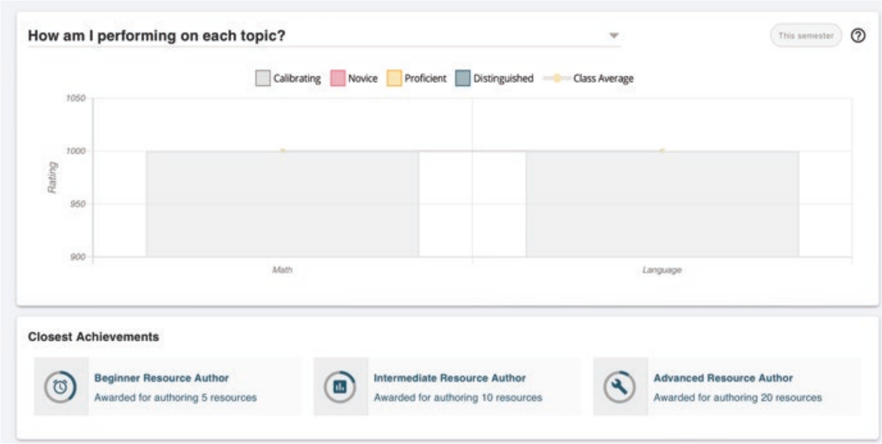

Fig. 9.7 RiPPLe user interface. As a student participates in taking and creating learning activities, a dashboard charts their progress/mastery and recommendations are made below for the next activities that are most relevant for them

gamification features into systems to boost voluntary participation, as discussed in Khosravi et al. (2020).

For the final part, the data-driven approach adopted by RiPPLE supports the management of the entire process of creation, curation and moderation of learner-sourced content. As discussed in Khosravi et al. (ibid.), RiPPLE intends to leverage artificial intelligence to help provide teachers with actionable and explainable insights. For example, RiPPLE makes heavy use of learning analytics inspired dashboards to give a facade to the masses of data that teachers can make sense of. Furthermore, their spot-check algorithm assists with quality management by identifying the content that is most in need of moderation which helps to reduce the timecost to the already time limited teachers involved in course management.

9.3.5 Evaluation, Reflection and Regulation

The fifth and final activity in the taxonomy is the use of students providing evaluation, reflection and regulation with other students' learning activities. Whilst peer review, peer teaching and peer instruction have been used repeatedly with success in academic many contexts and well reported in the literature, they normally are coarse in their granularity (e.g. peer review this report as part of your own assessment) or orchestrated (e.g. use of peer instruction in a lecture theatre) with teacher as conductor, or formalised in some way (e.g. use peer teaching using experienced students to tutor inexperienced students).

The learnersourcing perspective here is that these activities happen at a very fine level of granularity (e.g. rate this student generated question), ad-hoc with no

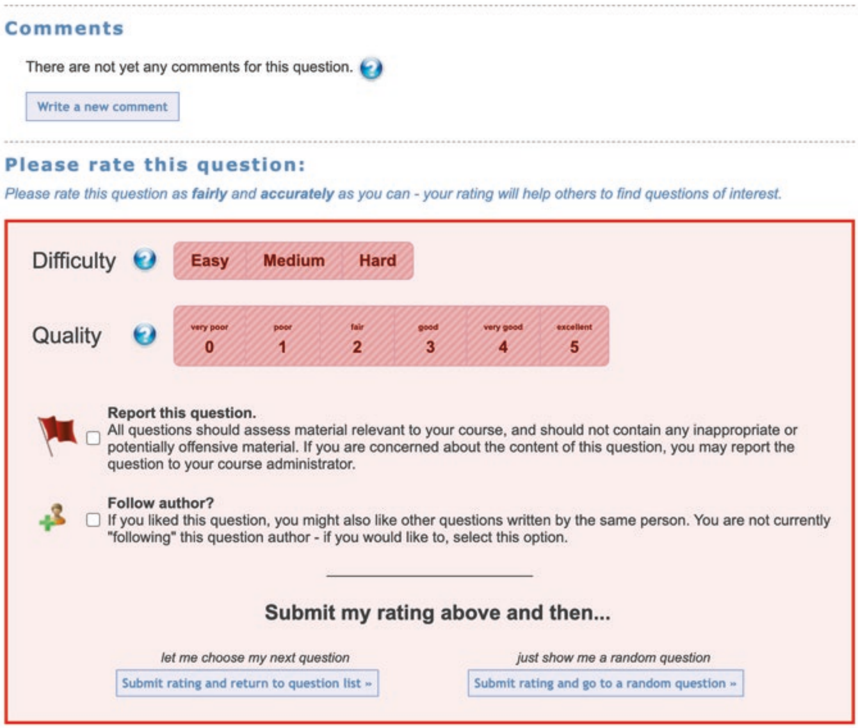

Fig. 9.8 Question feedback interface in PeerWise. Students can review and reflect on another student's question by adding open comments, as well as being able to rate the question in terms of its difficulty and quality

specific event or time-frame or guarantee (e.g. make the rating whenever you like), or informal to the extent that they are nice to have, but not deemed essential (e.g. only rate if you feel for it and want to make improvements). Learnersourcing platforms make it possible to engage in evaluation, reflection and regulation in effortless and optional ways.

Both PeerWise and RiPPLE are good examples of how student evaluation of learnersourced content can be integrated into the user interface of a learning platform. In the case of PeerWise, Fig. 9.8 shows a simple interface that allows students to provide a review of another student's multiple-choice question. First, they can leave open comments that both the author and future students can see. Second, they can leave ratings on difficulty (3-point scale) and quality (five-point scale). Finally, there is a flag option to check if the student believes that this question is either irrelevant or potentially offensive, which will notify the course responsible.

The RiPPLE platform allows students freedom to make all sorts of learning material, from simple questions to full assignments (Khosravi et al., 2021). Every time a student engages with content, they have the opportunity to provide ratings

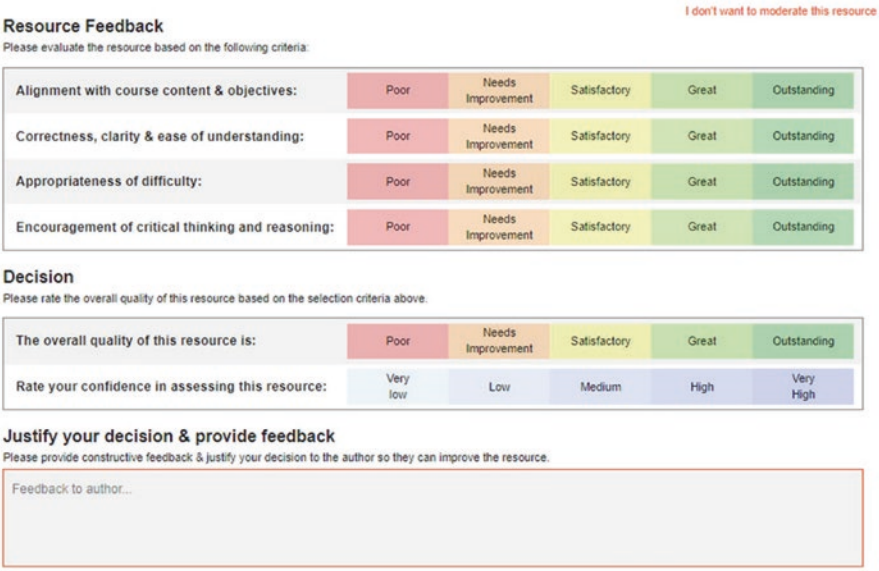

Fig. 9.9 RiPPLE content evaluation interface. Students are presented with a rich yet simple interface to help moderate content and improve the automatic processes that promote activities to students, whilst flagging those for moderation by teachers. (Adapted from Gyamfi et al., 2022)

and feedback as well as reporting serious issues that help with moderation, both using machine learning and moderation by teaching staff in the loop. The following examples and findings of evaluation, reflection and regulation can be found in the learnersourcing literature.

One common theme to all the former types of learnersourcing considered here (annotation, recommendation, explanation and creation) is that the quality matters and methods must be adopted to help filter the good and useful from the bad and unhelpful. To some extent, most of the literature surveyed here has touched on the topic of quality of content produced. Several more recent works have made quality the topic of focus and advanced differing mechanisms. In Darvishi et al. (2020) data-driven decisions that inform the design of learning materials are traditionally found to be related to student performance, that is, does student engagement with material lead to learning gains (and if not, what needs to be replaced, improved or removed). Instead, they propose a learner-centered strategy where the student is actively engaged in higher order learning tasks of giving their subjective reviews and ratings for learnersourced content. Again, asking students to evaluate their education, courses, effectiveness etc. is not novel (Chen & Hoshower, 2003), but by increasing the granularity down to evaluating individual tasks and presenting an interface that lets students express their view and see the views of others creates the step forward in quality improvement.

Once the door is open on including students in reviewing course content, whether learnersourced or teacher-produced, a new source of data for learning analytics appears in the form of the reviewer themselves – how do students perform when giving reviews, can quality of evaluation be determined, and how stable does this remain over time. Students are not experts in the task of evaluating content, but they can be guided with positive results, as reported in Gyamfi, Hanna, and Khosravi (2021). Just asking students to rate content will work out over time with the expected wide spread of quality, but by guiding students in terms of using rubrics can reduce the spread. When comparing no rubric, teacher developed rubric, and data-informed rubric based on prior student reviews, the data-informed version produced more rigorous evaluations and higher agreement in scores of quality (ibid.) – as shown in Fig. 9.9.

Beyond guiding students in their evaluation, the population of reviewers itself can generate insights into reliable and trustworthy reviewers that produce consistently good assessment of quality. In Darvishi et al. (2021) student reviews are not atomic, once-off events; neither can they be trusted at face value. Instead, a graph of trust and reliability is constructed from collective peer and instructor evaluations in order to both judge quality of content as well as the trustworthiness of the reviewers. Whilst limited instructor time was available to make corrections and spot checks, the approach adopted improved from the baseline system of independent reviews.

Whilst evaluation of content (and reviewers themselves) has received attention, more subtle aspects of reflection and self-regulation have been developed in the context of learnersourcing. In Huang et al. (2018) students working in a drawing course engaged in a form of learnersourcing that helped to generate reflection upon learning skills. Students used the ShareSketch platform to share their work with others. Part of this platform allowed students to also annotate their process as a

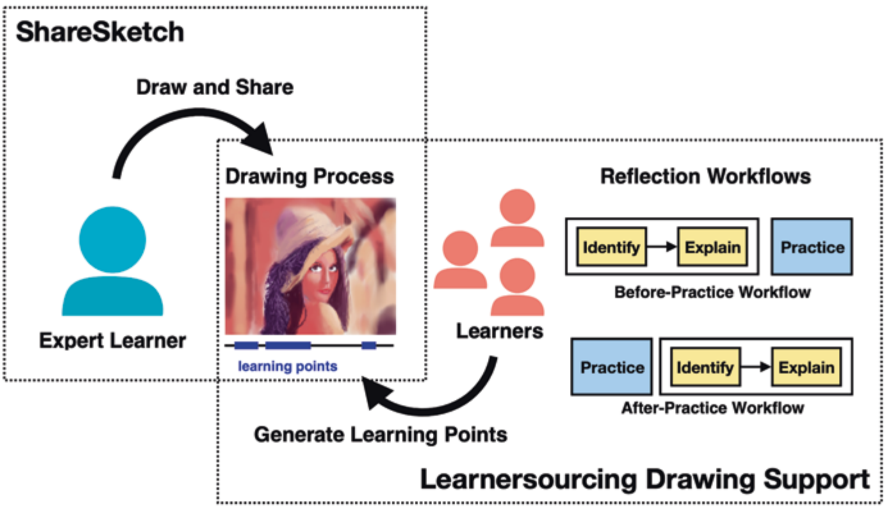

Fig. 9.10 ShareSketch user interface. Students not only can share the content that they make, but also their personal reflections to capture their learning points as they made a sketch. (Adapted from Huang et al., 2018)

reflective exercise on the content they had just produced – sharing details about what they learned in the process of practising (see Fig. 9.10). Unique to this work, these reflections are also shared on the platform so that other learners can in effect benefit from experiencing the reflection of others.

Finally, whilst platforms described throughout this chapter help students on their way to creating learnersourced content, there still remains the challenge that producing content should not be an exercise in futility if some students cannot produce content of a high or acceptable standard. Whilst moderating for quality and allowing the better content to shine, it is not particularly fair if students feel they put in effort but get no recognition. In Lahza et al. (2022) the authors investigated how strategies for self-regulated learning could be employed to help guide students through the production of content to increase the chance of producing higher quality work. In particular, different groups of students used scaffolding strategies (planning, externally-facilitated monitoring, self-assessing, or all three) compared to a control group. The findings showed that there were slight improvements to the quality, indicating that there is still much work to do in terms of incentivizing and guiding students to produce high quality learnersourced materials.

9.4 Summary and Challenges for Learning Analytics

As learnersourcing is an emerging and fast developing topic, this chapter has attempted to make a connection between learnersourcing and learning analytics in terms of the types of novel learning data that is produced. As the amount of educational data explodes as learnersourcing becomes more accepted into the mainstream practice of teaching, learning analytics will be essential to help manage, analyse, and produce new understandings from this shift in how students both produce content themselves as well as consume content created by others. The taxonomy presented here divided the current platforms and literature into five key types of activity: content annotation, explanations of misconceptions, resource recommendation, content creation, and evaluation, reflection and regulation. Each of these activities generates new and valuable collections of data to analyse with a learning analytics perspective, from the content created to the interactions surrounding engagement with that learnersourced content.

In spite of this positive opportunity at the intersection between learningsourcing and learning analytics, there are core challenges that must be tackled to make measurable progress in terms of the mutual benefits. We conclude this chapter with five challenges (or opportunities) that demand attention from researchers in this space: data, systems, participation, equity and ethics.

1. *Data*—The main motivation behind this chapter was to highlight the very novel and very relevant data that learnersourcing produces. There exists a range of shallow (simple voting on content) to deep (content creation) types of data that will very likely contribute to any form of learning analytics, complementing

existing approaches that target existing data trails that learners leave. However, this range needs more study from multiple aspects (learning science, computer science, cognitive science) to understand the role they play in learning.
2. *Systems*—As evidenced throughout this chapter, most learnersourcing research has been conducted upon prototype systems that are not integrated into traditional and widely adopted learning management systems. Less problematic is which learnersourcing activities are adopted, rather, having simple access to learnersourced data is critical in order for learner analytics techniques to be applied.
3. *Participation*—As with crowdsourcing, participation is very far from uniform in learnersourcing. Left as a voluntary activity the 90-9-1 effect of many passive, some active, and few very active kicks in. This creates an imbalance in data that could contribute to learning analytics, however more effort is needed in finding the best ways to incentivize or mandate learnersourcing activities and studies in this area are still too few in number.
4. *Equity*—Following on from participation is how fair analysing this type of activity might be – it is one thing to be asked to answer a question, which feels a normal part of education, but quite another to be asked to write the question for another. So far, most research has found positive results so perhaps this is not such a problematic issue, however there still exists a gap in our understanding of how fair it is (1) to ask someone to create learning content and (2) to have others engage with content that is not officially created or blessed by the course responsible.
5. *Ethics*—As a field of study learning analytics is intimately concerned with matters of ethics and this is no difference when the range of data that is considered for analysis extend to cover learnersourced data. The problem space here simply expands as more types of data are included and the future study of this intersection of topics must devote full attention to ethical concerns that arise from analysing learnersourcing activities.

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Chapter 10
Designing Culturally Aware Learning Analytics: A Value Sensitive Perspective

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10.1 Introduction

Learning analytics (LA) has been implemented and used in various countries in different ways, often at a limited scale (Viberg et al., 2018). Across countries and continents, there are differences in the expectations teachers and students have towards LA (Hilliger et al., 2020; Kollom et al., 2021; Pontual Falcao et al., 2022; Viberg et al., 2022), as well as different concerns about the ethical issues surrounding LA (West et al., 2018; Hoel & Chen, 2019; Mutimukwe et al., 2022). These differences make the transfer of LA solutions from one country to another challenging, i.e., varying contextual, technical, and also cultural factors may play an important role. Whereas technical and contextual aspects of LA systems' design and implementation have been addressed by LA scholars and practitioners, cultural factors have so far received scarce attention (Jivet et al., 2022). Paying attention to culture – both at the individual and also, at the national level – might be an endeavour worth exploring. As we argue later in this chapter, various cultural factors may influence students' or teachers' behavioural intentions and their eagerness to accept and adopt new technologies (Viberg & Grönlund, 2013). For example, already in

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1962, Rogers (1962) investigated various factors behind individuals' different levels of adoption of new technologies. He suggested dividing users according to their time to adoption (e.g., from the early innovators to early adopters). Scholars have studied different factors behind this time distribution, including gender, age, and technical skills, and suggested that many of them can have more than a temporal character. However, cultural factors have been argued to be more important since they are supposed to have more longevity, transcending the development of individuals (Viberg & Grönlund, 2013). This would make cultural factors highly interesting to consider and investigate in the LA setting even though they are often perceived to be challenging to study directly. As an alternative, they are often studied through some proxies, such as cultural values (e.g. Hofstede et al., 2010; Milberg et al., 2000).

The idea that a 'one size fits all' paradigm does not lead to effective LA tool designs and implementation has been accepted within both the technology-enhanced learning and the LA communities (Gašević et al., 2016; Teasley, 2017; Jivet, 2021). However, there is still a question about what factors define the 'right size', and throughout this chapter, we make a case for considering culture as one of these factors.

In this chapter, we argue that culture might play a role in the design of LA and discuss possible cultural differences – the factors that have so far not been extensively studied by LA researchers – for the wider successful adoption of LA at scale. In particular, this chapter discusses whether the stakeholders' (e.g., students' and teachers') *cultural values* are some of these factors. In an increasingly international educational landscape, how and to what extent should the LA community take into account such factors in order to have a significant impact (i.e., to improve learning and teaching) at scale? What opportunities are offered by LA technologies to consider stakeholders' cultural preferences and values, and how can we design culturally aware LA services which account for these values?

10.2 Why Is Culture Relevant for LA?

In general, a careful understanding of culture is important to the study of information technologies. Culture at various levels, including national, organisational, and groups, can influence the successful implementation and use of information technology (Leidner & Kayworth, 2006; Lee et al., 2013). This understanding is similarly critical to the successful implementation of LA systems to ensure equal and fair learning support opportunities for students from diverse cultures and in different educational settings. Cultural pluralism can lead to positive learning outcomes, including improved interaction skills, working relationships, and improved cognitive reasoning (Johnson & Johnson, 1989). At the same time, when not addressed appropriately, "cultural diversity in [collaborative] learning can lead to negative relationships characterised by hostility, rejection, stereotyping, and prejudice" (Economides, 2008, p. 249). Thus, we argue that culture and cultural differences should be considered in the design and implementation of LA solutions to both enhance learning and minimise adverse effects of culturally diverse learning environments.

While there have been some initial attempts to focus LA on cultural differences (Vatrapu, 2011), this critical topic is largely under-researched in current LA research and practice (Jivet et al., 2022). The research efforts on the topic point out at least three research directions. *First,* there are cultural differences in learning and teaching which will inevitably shape any LA used to analyse those processes, but also tools developed for these settings. Marambe et al. (2012) have, for example, shown that student learning patterns and learning strategies in higher education differ across cultures. Cultural differences were also shown to play a role in online learning settings as they influence students' collaborative learning (Vatrapu & Suthers, 2007), which is in line with broader research on culturally-aware collaborative learning (Economides, 2008) and self-regulation (Lin et al., 2021; McInerney, 2008; Purdie & Hattie, 1996).

Second, there are cultural differences in responses to LA related to, for example, adoption and the effectiveness of interventions. Nistor et al. (2013) showed that educational technology acceptance is influenced by culture with members of masculine cultures (cf. Hofstede, 2001) primarily expecting educational technology to improve their learning performance and members of individualistic cultures (cf. Hofstede, 2001) being less susceptible to social influence. Furthermore, Mittelmeier et al. (2016) found that cultural diversity explained a substantial part of the variation in learning dispositions, like boredom and learning enjoyment, as well as the use intensity of e-tutorials as part of a blended learning course. When analysing the effectiveness of interventions in the context of massive open online courses (MOOCs), Kizilcec and Cohen (2017) showed that a writing activity that facilitates goal-commitment and goal-directed behaviour raised educational attainment at scale in individualist (US and Germany) but not in collectivist cultures such as China. Later, Cho et al. (2021) examined the degree to which social norm messages can motivate people in different countries to persist in online learning and engage in their peer community and found that both the type of norm message (e.g., descriptive or injunctive) and the cultural context (China, US) influenced how the intervention improved course outcomes. Finally, Davis et al. (2017) showed that when learners are exposed to a learning dashboard that facilitates social comparison learners from countries with weak social norms and high tolerance for deviant behaviour significantly outperform their peers from countries with strong social norms and a low tolerance for deviant behaviour in terms of both engagement and achievement.

Third, LA can be used to study cultural differences in learning and teaching, especially in educational scenarios with culturally diverse populations. For example, Ruipérez-Valiente et al. (2022) found evidence that MOOC learners feel more comfortable and at ease when learning in their native language and having instructors with a similar cultural background, while Rizvi et al. (2022) have recently shown that certain types of learning activities (e.g., discussion) facilitate the progress of Anglo-Saxon learners while inhibiting the progress of learners from South Asia.

Overall, these examples show the importance of designing culturally aware or culture-sensitive (these two terms are used interchangeably in the present chapter) LA services that, as we argue, would increase the acceptance and adoption of LA at a global scale.

Cultural sensitivity is explained as “the competence to be aware of and to experience differences and similarities between people – their values and practices – and that they are based on what they have learned as members of groups” (Van Boeijen & Zijlstra, 2020, p. 20). Following this, the goal of the culture-sensitive LA designer is to know what the values, needs, and desires of the intended users (students and teachers) are, grounded in who they are as a part of the cultural group. Based on the earlier design-oriented research efforts in other fields (e.g., human-computer interaction), scholars suggest five possible intentions that offer a direction and are not a fixed outcome – as compared to aims or strategies – to be considered in dealing with culture (Van Boeijen & Zijlstra, 2020). They are: (**1**) to affirm a culture; (**2**) to attune to a culture; (**3**) to change culture; (**4**) to abridge cultures, and (**5**) to bypass cultures.

To affirm a culture in the LA setting suggests that the designer’s intention is to acknowledge and endorse the existing cultural values of the targeted users. Such values may include the stakeholders’ values of for example, collaboration, privacy, trust, transparency, and openness, which are all important to LA system development and an LA services’ further acceptance. For example, in strongly individualistic cultures like the US culture (Hofstede, 2001), this aspect could be upheld by way of LA services for highly individual and personalised usage. Another example refers to the different levels of individuals’ trust. In this regard, for example, the Nordic nations as compared to the originally more heterogeneous cultures such as the US, share a unique bond through cultural identity, creating an environment where these societies can exist with high levels of trust, transparency, and openness (Robinson, 2020a). Thus, the goal of the LA designer will be to affirm these values when designing LA services, and at the same time, to ‘protect’ users by undertaking a ‘responsible’ design approach that would enable their agency.

Attuning to a culture suggests that the designer intentionally “focuses on the attempt to be in tune with existing cultural values in order to achieve an optimal design and to avoid mismatches between the cultural group and the product” (Van Boeijen & Zijlstra, 2020, p. 25). In this, the LA designer may need to consider: *forms, colours, symbols, properties* (that describe the expected behaviour of the LA service under certain circumstances), *functions* (e.g., what the user can do with it; this can be specific for a cultural group), *interactions* (e.g., people have learnt to interact in some certain ways in some cultures, and in other ways in some other cultures; these interactions may be difficult to change), *needs*, and *values* (i.e., how people value a service or a tool is affected by the cultural context in which they have learnt what is morally right or wrong, or good or bad). In general, the design of a LA service needs to be attuned to the targeted culture(s) “to ensure it will be accepted or–even more critical–to ensure that it will be *loved*” (Van Boeijen & Zijlstra, 2020, p. 27).

To change a culture suggests that the LA designer will have the intention to change a current socio-cultural value by means of a design. Yet, when considering this intention, one should be attentive to the potential challenges related to pedagogy and the organisation of education as well as cultural values that the targeted population may share. Concerning pedagogy, any LA intervention needs to be positioned in the context of the selected teaching design and educational values that are important for this societal group and also for the targeted educational institution. As stressed by Knight et al. (2014), the "relationship between learning analytics and pedagogy is important because they are both bound up in epistemology – what knowledge is" (p. 29). For example, in the context of instructionalist approaches – that assume that learning entails the transfer of knowledge from the teacher to the student or the learner (such as in the societies with high power distance) – LA's focus will be on such basic metrics as test scores, not requiring "deeper analysis of more complex artefacts, or the processes by which they were derived (p. 30).

When aiming to change a culture, the designer may address the values (e.g., collaboration or trust) that are different from those that are largely accepted by the cultural group. For example, we know that some computer-supported collaborative learning activities may lead to the student's improved learning outcomes (Chen et al., 2018), but in some societies, they are not valued in the same sense as individual learning practices (Phuong-Mai et al., 2009) and related outcomes. The goal of the LA designer will be to approach the collaboration value in a way that would be easy to accept and desired by the targeted user, frequently the student or the teacher. The designer may assist in changing undesirable cultural assumptions or values, which are otherwise challenging and hard to change by for example, (1) making visible and tangible aspects of learning that were hard for people to articulate, and change, or (2) by introducing a dynamic that cultivates and also may sustain changes through for example, gamification.

To bridge cultures means to bring cultures together through design. In this regard, the LA designer will have an intention to elicit cooperation and respect between two or more cultures, or their selected dimensions (e.g., power distance or uncertainty avoidance) through design. One strategy can be to combine chosen values from both cultures and translate them into a new LA service.

Bypassing culture by design suggests that the LA designer will explicitly focus on the other aspects of design, such as the individual or universal perspective of human behaviour, the individual values of both teachers and students. That is, the LA designer should not have any culture-specific intention in mind.

Overall, a careful consideration of the design goals is critical to the successful design and implementation of LA systems. Moreover, considering the importance of understanding culture in the design and adoption of LA services, the complexity of the culture concept should not be underestimated.

One of the critical challenges in designing *culture-sensitive* LA systems and examining culture in LA research relates to an understanding of *what culture is*, given a considerable number of conceptualizations, definitions, and dimensions used to present this concept (Straub et al., 2002). Already in 1952, Kroeber and Kluckhohn identified 164 definitions of culture offered in the context of information systems research. Later, Sackman (1992) illustrated how culture can be framed in various studies as ideologies, coherent sets of beliefs, important understanding as well as basic assumptions. Further, scholars suggested that culture includes more observable, explicit artifacts such as norms and practices (e.g. Hofstede, 1998) as well as symbols (e.g. Burchell et al., 1980). Schein (1985a, b) presented a three-level model of culture uncovering the more observable aspects of cultures such as artifacts and the less observable facets such as *values*. Values represent "a manifestation of culture that signifies espoused beliefs identifying what is important to a particular cultural group" (Leidner & Kayworth, 2006, p. 359). In other words, these values may explain why learners or teachers behave the way they do when interacting with LA. Whereas the list of different definitions of culture presented above is not comprehensive, it provides some indication of the complex nature of culture. For the purposes of this chapter, we have chosen to approach culture from a *value-based approach,* further explained in the next section.

10.3 A Value-Based Approach to Culture-Sensitive LA Design

Even though individuals develop their cultural sensitivity through personal experiences of cultural encounters (e.g., how people collaborate or how they interpret various forms and colours), cultural sensitivity is an elastic concept that can be trained and learnt (Bennet, 2004). Culture-sensitive design is seen to be beneficial for several reasons, including the following: (1) to "cross the [cultural] chasm in order to connect": cultural sensitivity in this view will enhance one's empathy and respect for the people s/he is working with (e.g., the LA stakeholders); (2) to "gain a deep understanding of the users"; cultural sensitivity makes it possible to identify what is personal, what is affected by the cultural and societal setting, and what parts of human behaviour (e.g. learning patterns) are of general character; and (3) to "be inspired to find new ideas"; the designer may use cultural differences to elicit novel ideas (Van Boejen & Zijlistra, 2020, p. 30–31). Considering various definitions and conceptualizations of culture, this chapter employs a value-based approach. The values emphasized in a society may be "the most central feature of culture" (Schwartz, 2006, p. 139) as these values describe a shared understanding of what society views as good, right and desirable (Williams, 1970). For example, if a society values success and ambition, this might be reflected in "a highly competitive economic system […] and child-rearing practices that pressure children to achieve" (Schwartz, 2006, p. 139). In an educational setting, such an environment might foster competition among students as 'being better than your peers' defines a successful learner, encouraging the use of social comparison features in the design of LA dashboards (Jivet et al., 2017). We are only starting to understand how using social comparison as a reference frame is perceived and its impact on students as they use LA systems (Bennett & Folley, 2021; Lim et al., 2019).

Also, in some areas of the world, some values may prevail over others, and this will influence the adoption of technologies, such as LA and artificial intelligence. For example, Robinson (2020b) highlights that the Nordic countries are "unique with reportedly high levels" of trust, transparency and openness as cultural values; the high levels of all these three values create a unique cultural unity, creating requirements for implementing and adopting technologies where trust, transparency, and openness are crucial.

Here, it is important to stress that both cultural values and human values may affect the needs and expectations users have towards LA as well as the implicit biases designers may pack into the implementation of LA solutions. For example, designers, based on their experience, knowledge, and views, may intentionally or unintentionally embed their own (either individual or culturally learnt) values in the LA design process, which in turn may affect the adoption of the LA service negatively. Whereas human values refer to "what is important to people in their lives, with a focus on ethics and morality" (Friedman & Hendry, 2019, p. 4), cultural values refer to "collective tendencies to prefer a certain course of events above another, expressed by qualifications such as good and bad, dirty and clear, ugly and beautiful" (Hofstede & Hofstede, 2005). Overall, values are characterised by the following qualities: (i) values are conceptual, not physical artefacts; (ii) they are not always explicit – one might act in accordance with values without being fully conscious of them; (iii) values must be acted on (e.g., through the study of the student or teacher's behaviour, and (iv) values consist, at their core, of "the desirable", in the sense of what is righteous (Jorgensen, 2007).

10.4 Privacy and Autonomy in LA: A Value-Based Approach

A culturally aware LA service could reinforce or support certain values and hinder others, depending on the intentions of the designer or other factors such as stakeholders' motivation and the targeted context. For example, a LA dashboard that shares any student's progress with their peers might support the individual's learning progress but impinge on student privacy. Further, the implemented LA system may lead to improved learning outcomes for only some students. At the same time, students and teachers may trust such a system less if they were not consulted before the development was considered. While there are many values that could be considered by the LA designer (e.g., autonomy, community, fairness, equity, human dignity, inclusivity, informed consent, justice, privacy, self-efficacy, and trust), for the purposes of this chapter we have chosen to discuss two of them, namely *privacy* and *autonomy,* given the research efforts and attention given to privacy and self-regulated learning in the field of LA (Drachsler & Greller, 2016; Winne, 2017; Matcha et al., 2019). To complement the extensive research surrounding these two values within LA, this chapter aims to offer new insights that a cultural values-centric lens brings to these two extensively discussed topics.

10.4.1 Privacy

Privacy is an elastic and complex concept and value that is associated with various definitions and interpretations. For instance, Westin (1967) defines privacy as the "desire of people to have the freedom of choice under whatever circumstances and to whatever extent they expose their attitude and behavior to others". Belanger et al. (2002) suggest that privacy refers to one's ability to control information about oneself. Further, scholars have argued that privacy represents the control of transactions between person(s) and other(s), the ultimate aim of which is to enhance an individual's autonomy and/or minimize potential risks (Dinev & Hart, 2004). Overall, Smith et al. (2011) in their review of privacy in information systems research have earlier found two key definitional approaches to privacy: cognate-based and valued-based. From the cognate-based view, definitions of privacy relate to privacy as a state and privacy as control. The control-based definition has gotten into the mainstream of privacy research, "likely because it lends itself more readily to the attributes of information privacy" (Smith et al., 2011, p. 995). The value-based approach sees privacy as a human right integral to society's moral value system. From the value-based perspective, privacy is overall defined as a right, and also, as a commodity.

Overall, how individuals perceive privacy as a cultural value can vary across societies. In this regard, earlier research in information systems has shown that cultural values – measured through the overall value of four cultural value indices: Power Distance, Individualism, Masculinity and Uncertainty Avoidance (Hofstede et al., 2010) – had a significant and positive influence on individuals' privacy concerns across countries (Milberg et al., 2000). This has been explained in the following way: although cultures with a high power distance index tolerate. Greater levels of inequality in power, higher scores are associated with greater mistrust of more powerful groups, such as organisations or institutions. Further, cultures with a lower individualism index (i.e., collectivistic cultures), such as China, have a greater acceptance that groups, including organisations (e.g., universities), can intrude on the private life of the individual. This can directly have implications for the integration and acceptance of LA systems in some cultural contexts, but at the same time, impinges on the stakeholders' privacy. In the LA context, Hoel and Chen's (2019) findings demonstrate that there are problems using privacy concepts found in European and North-American theories to inform "privacy engineering" (i.e., "a systematic effort to embed privacy relevant legal primitives into technical and governance design", Kenny & Borking, 2002) for a cross-cultural market in the era of Big Data. That is, theories that are grounded in individualism and ideas of control of private information do not capture current global digital practice. Further, they raise the importance of a contextual and culturally aware understanding of privacy to inform "privacy engineering" without sacrificing universally shared values. In the process of "privacy engineering", the governance and work practices around it should be considered.

10.4.2 Autonomy

Etymologically, autonomy comes from Ancient Greek, with *autos* meaning self and *nomos* meaning law and defines the "ability to make your own decisions without being controlled by anyone else" (Cambridge University Press n.d.). Ryan and Deci (2006) argue that autonomy is a fundamental and universal human need and was one of the foundational stones on which self-determination theory was built. Autonomy is seen as a dominant value of the Western world, being central to political definitions of democracy (Blomgren, 2012) or health care decision-making (Elliott, 2001; Gilbar & Miola, 2015). In a learning context, *autonomy* refers to "the extent to which students have choices about what to do and when and how to do it" (Schunk, 2012, p. 255).

Several scholars expressed doubts about the universality of autonomy across cultural contexts. For example, cross-cultural psychologists argue that autonomy is valued less by Eastern learners and question the benefits of striving for learner autonomy (Iyengar & DeVoe, 2003). At the same time, other works reveal that autonomy is connected to well-being (Chirkov et al., 2003) and study success (Vansteenkiste et al., 2005) across all cultures. As a way of explaining this discrepancy, Chirkov et al. (2003) hypothesized that autonomy can be enacted differently in different cultural settings due to diverse contextual conditions. Keller (2012) proposed the same explanation and distinguished between psychological autonomy, i.e., "psychological control over intentions, wishes, and actions" (p. 16) more prevalent in Western-urban environments, and action autonomy, i.e., "the responsibility to perform actions in a self-reliable way" (p. 16) in rural, subsistence-based farming families.

For the purpose of this chapter, we illustrate the value of autonomy by answering the question, *Who makes decisions with LA?* We briefly discuss two instances in the context of LA design where cultural influences are worth considering: (1) a machine is making decisions instead of a human, and (2) a teacher is making decisions instead of a student. These two instances map to the two ways of using LA and educational data mining to build systems that process data and (1) make decisions automatically based on the outcomes (e.g., intelligent tutoring system, adaptive systems) or (2) report the outcome directly to the stakeholders and thus leverage human judgment (e.g., with dashboards) (Baker, 2016).

Firstly, in the case of 'human vs machine', technology acceptance might impact the willingness of teachers or learners to delegate the decision-making to (intelligent) systems. The technology acceptance model (TAM) is a widely used model to understand what factors predict human acceptance or rejection of technology (Venkatesh et al., 2003), even in educational settings (Granic & Marangunis, 2019) or to investigate the readiness of teachers for LA (Ali et al., 2013; Rienties et al., 2018). In this model, external variables influence the perceived usefulness and the perceived ease of use, which in turn shape behavioral intentions and lead to the actual use of the system (Venkatesh et al., 2003). TAM was developed in the US and was widely used across cultures, but there is some evidence that TAM might not hold in all cultures (Srite, 2006), as certain cultural orientations "nullify the effects of Perceived Ease of Use and/or Perceived Usefulness" (McCoy et al., 2007, p. 81).

Undoubtedly, *trust* is another factor that influences learners' and also teachers' willingness to allow systems, AI educational technologies, in particular, to make decisions for them (Nazaretsky et al., 2022). As cultural norms and values shape trust in human relationships (Doney et al., 1998), they also hold human trust and attitudes towards automation (Chien et al., 2016). Thus, next to digital literacy, culture could also play a role in LA design decisions around who should retain the power of decision, who would take responsibility when the system makes a mistake (Santoni de Sio & Mecacci, 2021), and how the system communicates the educational values the school is supposed to teach.

Secondly, one can look at the interplay between cultural values, the teacher-student relationship, and expectations around LA. Over the past years, there has been a strong focus on supporting self-regulated learning through LA (Winne, 2017; Viberg et al., 2020), enhancing and developing autonomy in students, and equipping them with skills to become masters of their own learning. Again, this focus has been shaped in the Western context from a Western perspective. As previously mentioned, research suggests that autonomy might benefit all students, regardless of their cultural background. Initial work exploring teachers' expectations across continents has shown contrasting outcomes. While in Europe teachers expect LA to enable decision-making on the student side (Kollom et al., 2021), LATAM teachers find more value in LA tools supporting teacher decision-making (Pontual Falcao et al., 2022). LA – as an educational research tool – can be designed to provide computational proxies for student levels of SRL (e.g. Viberg et al., 2020). That is, it could be used to help investigate if there are cultural differences in student SRL. Furthermore, if LA can then be used to support students, e.g., through the provision of feedback on SRL, then one can study the differential effects of doing so with different student cultures. This in turn may connect with feedback literacy, i.e., learner disposition and skills of actively seeking out and engaging with feedback (see e.g., Lim et al., 2021). In sum, these are just a few examples that showcase the importance of considering cultural differences when designing and implementing LA systems across countries.

10.5 Future Research Directions

Based on the argumentation and a scoping review of the literature presented in this chapter, there are several future research directions to be considered by the LA community.

Grounded in the extensive research on culture in the established field of information systems research (for an overview, see Leidner & Kayworth, 2006), LA scholars need to look into the question of how culture influences stakeholders' requirements for LA systems' design. Here, it is important to consider different levels of culture, including national and organizational ones (e.g., educational institutions often have their own cultures). One challenge relates to the assumption that all individuals within a selected cultural unit will respond in a consistent way based on the group's cultural values; this view limits individual differences that may be found within a particular cultural unit (e.g., a school) that may lead to different behavioural outcomes. To better understand such differences, the application of person-centric approaches (Hickendorff et al., 2018) offers a solution.

Further, when conducting related cross-cultural studies (e.g., evaluating the use of a selected LA tool in the selected contexts) LA researchers need to address three types of methodological bias – found in other information systems-culture research (Leidner & Kayworth, 2006). First, there is *construct bias*, suggesting that a given concept or cultural value (e.g., privacy) is not viewed similarly across contexts. Second, there is *method bias*, i.e., when study participants across cultures and countries do not respond similarly to measurement scales due to factors linked to demographics or the administration of the instrument. And finally, there is *item bias* that derives from the poor translation of the (survey) instrument.

10.6 Conclusion

In this chapter, we argued how culture can play a role in the design of LA and proposed that addressing factors such as stakeholders' cultural values can influence the successful adoption of LA at scale. We stressed the importance of the cultural setting, and the range of intentions designers can have when dealing with culture (affirming, attuning, changing, abridging, bypassing) as this helps to set the tone for the envisioned LA system. We then specifically looked at two cultural values, i.e., privacy and autonomy, to exemplify how such values might affect the requirements for and the design of LA systems.

Based on the argumentation provided above, we outline several design implications for culturally aware LA, mainly aimed at learning (analytics) designers. Nonetheless, these suggestions could also be followed by teachers adopting LA solutions in their classes.

First, designers who aim to develop culturally-aware LA solutions need to start with the definition of culture and values. This can be achieved through the examination of existing understandings of culture and values, both in research and practice. Such definitions can be also offered by stakeholders (students and teachers).

Second, when designing culturally aware LA systems, designers need to consider and differentiate between individual and cultural *educational* values. Although a group's culture might shape the values of its members, personal values among the individuals of the same group vary.

Third, there is a need to keep the design intention in mind, for example, whether the suggested LA system aims to affirm cultures or bridge them. This is important to consider from the very start of the design process. This decision can be informed by key stakeholders directly, which relates to the need to use participatory design and co-design approaches for a more likely adoption of LA systems (see e.g. Sarmiento & Wise, 2022).

Fourth, designers could consider using existing culturally aware and value-sensitive design methods, originating in other disciplines, such as human-computer interaction in the LA design process. Such methods include direct and indirect stakeholder analysis, stakeholder tokens, value-source analysis, value scenario, and value-oriented semi-structured interviews (Friedman & Hendry, 2019).

And finally, *fifth*, one should pay attention to the fact that culture and values (such as privacy) are elastic concepts and may change over time. This is important to keep in mind to be able to adapt to the stakeholders' views, needs and preferences concerning the implementation of LA systems. In this regard, the application of for example, Design Science Research methodology (DSR; Hevner et al., 2004; March & Smith, 1995; Vaishnavi & Kuechler, 2008), also valuable in education settings (Laurillard, 2012) can be helpful.

To conclude, we would like to stress the importance of looking at culture in a global educational landscape that is ever increasing without reducing learners to their culture. Our intention is not to suggest that individuals can be prescribed a certain type of (learning) analytics based on their culture, but rather to cultivate an awareness of the influence that cultural values might have on the perceptions and preferences of both learners and teachers.

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Chapter 11
Challenges and Recommendations on the Ethical Usage of Learning Analytics in Higher Education

Anna Mavroudi

11.1 Introduction

Higher education actors have shown an increased interest in deploying Learning Analytics (LA) in their respective institutions, while research continues to shed light on LA benefits. A recent scoping review (Quadri & Shukor, 2021) mentions the most important ones for the higher educational institutions, such as monitoring of students' dropout and retention, and improving tutors' performance. LA refers to "the process of measurement, collection, analysis and reporting of data about learners and their contexts" (Siemens, 2012, p. 4). The hidden link between the premises of Quadri and Shukor (2021) and the definition of LA set out by Siemens (2012) is that LA can monitor and predict students' performance. In turn, this can provide the opportunity for the tutor to identify which students perform poorly in which subject-matter areas. This enables the tutor to obtain a better understanding of the students that are facing problems and thus, to intervene timely; something that could prevent students from failing the course or from dropping out. Yet, student failure (i.e. how it is conceived) and the type of tutor intervention are both context-dependent; for example, in the case of Arnold and Pistilli (2012) LA assisted teachers to provide real-time feedback to students at risk of not reaching their potential. An algorithm using as input a set of context-dependent factors (student performance, effort, academic history, and demographics) determined the risk level for the individual student.

Ferguson and Clow (2017) argue that LA can improve learning practice in higher education institutions (HEI) based on four propositions: (1) they improve learning outcomes, (2) they support learning and teaching, (3) they are deployed widely, and

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(4) they are used ethically. This chapter revolves around the last aspect focusing on the ethical uses of LA in higher education. A recent systematic review by Viberg et al. (2018) revealed that only 18% of the research studies mention “ethics” or “privacy”. The authors of the review argue that this is a rather small percentage considering that empirical LA research should seriously approach the relevant ethics and they call for a more explicit reflection on the topic. In relation to that, Tsai and Gasevic (2017) mentioned the lack of research work with respect to appropriate LA policies on ethics and privacy as one of the main challenges that hinder LA adoption in higher education.

Concerning the scope of this chapter, it considers the ethical uses of LA suggested by the research literature as well as by non-academic sources. In addition, it examines the respective policies at several selected universities in three countries that have a long tradition and presence in the use of LA in higher education: the UK, Canada and Australia. Nine universities were selected based on three criteria: (1) both traditional and distance education universities should be included (seven traditional and two distance education universities), (2) they have public policies written in English that freely accessible online, and (3) they are geographically distributed (three different continents).

The aim of the chapter is to contribute to the ongoing discussion about the topic of ethical issues pertaining to LA use in higher education by providing insight and critical reflections on the different challenges that might interplay and how different policy frameworks address these challenges. In doing that, the chapter focuses on and discusses three common aspects concerning ethical use of LA in higher education: transparency, access, and privacy. The analysis and the discussion focus on these particular aspects as well as on the corrective measures in LA policy frameworks at the selected higher educational institutions to address associated challenges.

11.2 Background

The ethical use of LA in higher education is a multifaceted and complex task. There are many ethical dilemmas associated to it today (Slade & Prinsloo, 2013). Tzimas and Demetriadis (2021) touch upon LA ethics as a field of study by unpacking its concept, but also any contradictory viewpoints emerging among the several stakeholders in a university. Concerning the former, they present LA ethics as a field that addresses moral, legal, and social issues that apply to educational data of any size. Concerning the latter, they present several examples, such as the importance of striking a balance between the availability of student data and limitations imposed on it. Also, the contradiction of using deterministic data-driven algorithms to capture evidence of learning in line with learning theories, which are more complex than behaviorism. Slade and Prinsloo (2013) mention several ethical challenges related to the collection and use of digital student data associated to several processes, such as interpretation, informed consent, privacy, de-identification, and management. Although HEIs have committees with expertise on how to carry out endeavours involving the collection of personal student data or conducting research using such data, LA poses some new conditions. For instance, the ethical issue of equity of treatment, that is, the fact that additional resources and guidance are being directed to just some students (e.g. students at risk of falling out), but not to all of them (Scheffel et al., 2019). Also, one relevant condition involves ensuring data privacy in the case of implementing LA interventions that call for personalised assistance or guidance to the student. Still, a systematic review focusing on the intersection of personalised learning and the use of LA revealed that most studies did not mention how they ensured data privacy or data security (Mavroudi et al., 2018). Adding to that complexity, the new General Data Protection Regulations (GDPR) came in effect in 2018 in EU and EU-associated countries and along with that many potential consequences on LA research and practices (Karunaratne, 2021), such as the importance of the possibility for a student to opt-out from a LA endeavour without stating any reason for that.

According to the literature, principles frequently related to LA deployment policies are (Slade & Prinsloo, 2013; Pardo & Siemens, 2014; Steiner et al., 2016): informed consent, privacy, de-identification of data, transparency, student control over data, the possibility of error or bias and associated concerns of LA interpretation, right of access to one's records of data, accountability, and the right to opt-out. One influential relevant framework that manifests these principles is the code of practice for LA launched by the UK Joint Information Systems Committee in 2015 (JISC, 2015). In addition, the framework mentions the importance of minimizing adverse impacts and enabling positive interventions. Yet, the definitions, interpretations as well as the implications of these principles are still elusive for many. For instance, Prinsloo and Slade (2018) challenge the notion of consent in the digital arena as well as the notion of control over one's data. Furthermore, it has been suggested that it is almost impossible to define the concept of privacy in the context of LA (Prinsloo & Kaliisa, 2022). Still, there exist context-dependent definitions of the notions of these principles (ibid) in relevant LA policy documents of higher education institutions, or codes of ethics for LA in HEIs. Consequently, in the context of this chapter the main concepts are understood as follows:

– *Transparency* is mostly understood in two ways: transparency related to human judgement and transparency related to automated decision-making. The former type pertains to processes that enable stakeholders (and first of all, data subjects that is, individual students) to make informed decisions on LA held about them by providing to them clear and timely information about the parties have access to data, the data collected, and the ways that they visualised (Tzimas & Demetriadis, 2021). The starting point of this type of transparency is transparency of purpose i.e. why will LA benefit the data subjects. The latter type relates to transparency in automated decision-making. Automated decision – making is realised through the processing principles of machine learning and predictive models embedded in LA systems and it is often referred to as algorithmic transparency (Karunaratne, 2021). There is a dialogic relationship between these two types of transparency, which is nicely manifested in the GDPR context. GDRP

caters for transparency related to human judgment, but it also secures algorithmic transparency by linking it to the right of the data subjects to know all the related information on "the existence of automated decision-making, including profiling and [...] meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject." (GDPR, 2018)
- *Access* involves primarily students' right to access all LA performed on their data in meaningful, accessible formats, and to obtain copies of this data in a portable digital format (JISC, 2015). Students have a legal right under the GDPR to be able to correct inaccurate personal data held about them (JISC, 2015). In more generic terms, this principle requires that the respective LA policy describes the type of operations allowed in the LA dataset and also which users have access to which areas of the LA application (Pardo & Siemens, 2014).
- *Privacy* is defined as "the regulation of how personal digital information is being observed by the self or distributed to other observers" (Pardo & Siemens, 2014, p. 438). In the specific context of LA, it involves restricted access to those identified by the institution as having a legitimate need to view the respective LA datasets. If LA are used anonymously, care must be taken by higher education institutions to avoid identification of students from metadata and re-identification by aggregating multiple data sources (JISC, 2015).

11.3 Limitations of LA Mentioned in the Literature

Tsai and Gasevic (2017) identified in the literature six LA challenges related to strategic planning and policy in the context of higher education. The lack of policies that address LA privacy and ethics issues was among them. With respect to ethical issues, their findings indicate that the analyzed policies included relevant considerations of data identification, data access, informed consent, and the possibility to opt out of data collection. Wilson et al. (2017) stresses the difference between capturing students' activity in some digital environment and capturing evidence of student learning, in effect, the difference between accessing a digital learning resource and meaningfully engaging with it. The authors refer to the former type of analytics as 'activity analytics' which act as 'questionable proxies for learning' and they outline limitations such as conflicting outcomes from empirical LA studies on predictive analytics. Predictive analytics are LA types which "are used to identify learners who may not complete a course, typically described as being at risk" (Herodotou et al., 2019, p. 1273). Furthermore, the authors mention potentially biased algorithms, the ethics around personalised guidance, and disciplinary differences. Similarly, both Wilson et al. (2017) and Ellis (2013) have raised concerns on the pedagogical meaningfulness of what can be captured via LA. For instance, Ellis (2013) argues that LA is not possible in face-to-face learning sessions that still prevail in higher education institutions because the learning interactions and the learning outcomes cannot be capture in these sessions. Thus, making judgement about student engagement solely from LA evidence sources is not valid. In general, Ellis (2013) posits that LA design and decision-making should be led by pedagogy and not by data. The overall conclusion with respect of LA challenges is that of equating student activity as assessed via LA in a digital learning ecosystem with student engagement. In turn, this conveys the idea that student performance and engagement should not be characterised solely by information on their LA profile.

Furthermore, one of the most crucial barriers of LA adoption in higher education touches upon the presence of biases, either associated to the design of the LA algorithms or to the human judgement and decision-making that stems from using LA – or from both (Uttamchandani & Quick, 2022). In relation to that, several researchers have stressed the need for methods in identifying and dealing with biases in LA (Pelánek, 2020). A recent empirical study examining university students' attitudes towards LA revealed that the potential of bias was one of the main ethical concerns raised by the students (Roberts et al., 2016). In addition, the recent relevant literature pinpoints to an interesting tension between empowering learners via personalised learning approaches enabled by LA on the one hand while diminishing their agency in the LA lifecycle process on the other hand (Tsai et al., 2020). In other words, how many degrees of freedom do university students have in being actively involved in all the phases of the LA lifecycle? Another relevant and interesting problem that arises is whether the lack of students' active involvement manifests asymmetrical power relationships between higher education institutions and students (Slade & Tait, 2019). And if so, whether that could inhibit the principles of transparency and access?

Finally, insufficient university staff training and professional development of tutors are frequently mentioned in the literature are barriers of meaningful LA adoption. For instance, Tsai and Gasevic (2017) mention the importance of data literacy skills needed to evaluate the impact and the effectiveness of LA.

11.4 The Central Concepts Manifested in LA Frameworks at the Selected HEIs

The focus of this section is firstly on the ways that the selected LA policy framework integrate the main concepts (transparency, access, privacy) discussed in the previous section. The remaining of this section presents selected points of each framework with respect to these concepts. It also provides secondarily a few relevant comments and interesting points from each framework, for example, about how the respective framework addresses uncertainties/problems with LA.

Interestingly, a few elements are common in all frameworks:

- A description of how the frameworks facilitate transparency of purpose (transparency)
- That students have the right to request a copy to see their data (access)
- The LA privacy policy builds on the generic privacy policy concerning data privacy (privacy).

(These are taken for granted hereafter and thus they not repeated in Sects. 11.4.1, 11.4.2, 11.4.3, 11.4.4, 11.4.5, 11.4.6, 11.4.7, 11.4.8, and 11.4.9). Furthermore, all selected higher education institutions introduce their respective framework of ethical use of LA with a description of how it aligns with core organizational principles and values.

11.4.1 The Open UK

According to the policy of Open UK (2014a, b)

- the LA privacy policy adheres to a wider university privacy policy which covers topics such as timeframe for retaining personal data, de-identification, and consent
- algorithmic transparency focuses on statistical models that use standard techniques which can be reviewed and tested
- students do not have the right to opt-out from LA interventions (in the sense that students cannot ask to exclude data about them)
- Students can update their personal data.

Other points: Modelling and interventions based on analysis of data should be sound and free from bias; predictive analytics reflect on what has happened in the past to predict the future, thus attention should be placed on calculation of error rates, the acknowledgement of atypical patterns, and guarding against stereotyping.

11.4.2 University of Edinburgh, UK

According to the policy document of the University of Edinburgh (2018).

- algorithmic transparency is seen a requirement to be assured during procurement of external services
- students can access and correct any inaccurate personal data held about them.
- the LA privacy policy adopts the already existing wider data privacy statement which caters for data security and restricting access.
- access and privacy are examined under the legal basis of legitimate interest.

Other points: it is crucial that the analysis, interpretation and use of the data does not inadvertently reinforce discriminatory attitudes or increase social power differentials; potentially adverse impacts of the analytics and steps taken to remove or minimise them.

11.4.3 University of Glasgow, UK

According to the policy document of the university (n.d.)

- LA lifecycle processes should be transparent to all stakeholders
- students have the right to rectification of personal data held about themselves
- students have the right to opt out
- the GDPR also raise questions about who has access to data stored in third-party platforms
- privacy and access are examined under the legal basis of on legitimate interest.

Other points: recognition that LA data does not give a complete picture of a student's learning; interventions or actions stemming from LA must be inclusive.

11.4.4 Central Queensland University (CQU), Australia

The CQU policy and procedure document (2021) refers to:

- transparency (which data sources are used, how LA are produced, how students may use LA, and the type of interventions that employees may implement) coupled with student consent
- de-identification of information kept about students to protect privacy
- access restricted to those that have a legitimate interest
- the students' right to rectification of personal data held about themselves.

Other points: Training and professional development on LA for university staff to minimise the potential for adverse impacts; recognition that LA data does not provide a complete picture of a student.

11.4.5 University of Sydney, Australia

The university has adopted a policy (2016) that caters for:

- students' right to access and correct LA data about them
- students' right to be notified about privacy breaches and file a formal complain
- de-identification of (statistical) data and associated privacy concerns
- transparency of how LA will be collected, used and disclosed.

Other points: regularly reviews of LA processes to ensure relevance with the university goals.

11.4.6 University of Wollongong, Australia

The policy of the university of Wollongong (2017) is characterised by:

- transparency on data sources, the purposes, the metrics used, different access rights, the boundaries around usage, and data interpretation
- algorithmic transparency that focuses on how predictive analytics algorithms should be validated, reviewed and improved by qualified staff
- students' right to access and correct personal data about them,
- access rights and restrictions for all stakeholders including external ones
- not complying with the students' right to opt-out of inclusion in LA initiatives.

It should be mentioned that the last point is due to the duty of care obligation towards students enacted by monitoring student progress towards learning goals. (The same applies for the case of Open UK, Sect. 11.4.1).

Other points: minimizing adverse impacts, which relates to recognition that LA data does not provide a complete picture of a student and to the fact that opportunities for "gaming the system" are minimised.

11.4.7 Athabasca University, Canada

The Athabasca University in Canada has adopted a comprehensive set of principles for ethical use of personalised student data (2020) which is in line with:

- transparency on LA lifecycle processes and associated data accuracy controls
- transparency on data sources and datatypes collected
- privacy in connection to the "data-minimization" principles.

Other points: consideration of potentially de-motivating effects is required so that LA can help towards supporting and developing student agency; benefit all students (not just at-risk students) in enhancing their academic achievements via LA interventions.

11.4.8 University of British Columbia, Canada

The UCB policy (2019) highlights:

- students' agency and their active role as collaborators and co-interpreters of LA (as opposed to just being able to see and access LA or passively receive recommendations)
- algorithmic transparency especially in the case of predictive analytics algorithms (they should be validated, reviewed and improved by qualified staff)
- "data minimization" (i.e. accessing only what is necessary) as a means to mitigate the effects of biases.

Other points: acknowledge the possibility of unforeseen consequences and mechanisms for redress; benefit all students (not just at-risk students) in enhancing their academic achievements via LA interventions.

11.4.9 University of Alberta, Canada

The university has adopted a code of ethics (2020) focuses on:

- algorithmic transparency especially in the case of predictive analytics algorithms (they should be validated, reviewed and improved by qualified staff)
- informed consent and the possibility to opt-out (privacy self-management)
- students must be able to access their data and to correct any inaccurate personal data held about them
- access based on legitimate interest
- re-identification of data and data anonymization whenever possible.

Other points: inaccuracies in LA data are understood and minimised, and misleading correlations are avoided; the implications of incomplete LA datasets are understood; adverse impacts are minimised i.e. recognition that LA data does not provide a complete picture of a student, opportunities for "gaming the system" are minimised on behalf of the students.

11.5 Discussion and Conclusions

Theoretically, LA holds the promise of promoting the effectiveness of teaching and learning at a large scale in HEIs. There is research work in the LA field providing ample empirical evidence on that. Yet, in practical terms, there are associated ethical challenges that hinder the adoption of LA at a large scale in HE. This state of affairs coupled with the willingness of the research and the educational community to provide solutions to the emerged ethical challenges has motivated the LA research community and the HEIs to work on the ethical concerns: to identify them, and to address them by suggesting proactive and/or corrective measures. The chapter discusses challenges of LA ethics mentioned in the relevant literature as well as by external to the universities organizations, such as JISC that provided one of the leading frameworks in 2015 which still inspires HEIs policies.

The chapter aimed to: (1) identify and define the main theoretical concepts that pertain to the ethical use of LA in HEIs (e.g. transparency, privacy, access), (2) identify and critically discuss principles and limitations associated to these theoretical concepts, and (3) analyse relevant policies in several HEIs coming from three continents (Europe, America, and Australia). The policies adopted by the HEIs included in the review addressed issues that were revolving around the skepticism and the associated ethical challenges of LA deployment mentioned in Sections 11.2

and 11.3. All the main concepts that pertain to ethical issues of LA use in HEIs are tackled in the policies. That does not mean that all policies address equally well all the main issues. This is an expected finding, since the LA policies are fully in line with contextual parameters in HEIs governance such as the vision, the mission, and the core institutional values of the respective HEIs.

All frameworks were characterised by four common elements: (1) a description of how the policy aligns with the principles and values of the respective university, (2) a description of how the framework facilitates transparency of purpose, (3) granting to the students the right to request a copy to see their data, and (4) a description of how the LA privacy policy builds on the wider university policy concerning data privacy. Perhaps then we could consider these core elements as the starting point of an LA policy on ethical uses for higher education institutions.

With respect to transparency, the most basic measure that the HEIs should take is to clarify transparency of purpose by providing proper justifications to all stakeholders on the reasons that lead to embarking into an institution-wide LA analytics endeavour. Besides that, a critical examination of the selected frameworks shows that transparency is understood by its two main aspects: transparency related to human judgement and algorithmic transparency. The former relates to the transparency of communicating all the main processes of LA lifecycle to all the main stakeholders in the most effective way. As a means to encourage this type of transparency, the policies suggest as a good practice effective communication between all the stakeholders involved with the aim of providing information on: the sources and the metrics used, the purpose, different access rights, and data interpretation. The latter relates to the design of LA algorithms. Two main measures are proposed in the examined policies to encourage algorithmic transparency. Firstly, LA algorithms based on standard statistical techniques that can be transparent, tested and audited from the HEIs. This applies especially to predictive LA. Secondly, proposing algorithmic transparency as a procurement requirement for external stakeholders (e.g. learning management system providers). In general, it can be concluded from the above that a holistic framework addresses all the different aspects of transparency that stem from its definition (Tzimas & Demetriadis, 2021). Yet, addressing equally well all these different aspects seems to be a resource-intensive endeavour that calls for expertise that might be difficult and costly to find and recruit internally, especially in a small HEI.

With respect to access, the most interesting finding is its conceptual connection to student agency. What makes this connection the most interesting one, is that (a) it seems to be less apparent than other ideas that one could directly associate to the concept of access, such as one's right to view the LA dataset about themselves and (b) it was not explicitly discussed in the majority of the frameworks presented herein. A critical analysis of the frameworks presented in Chap. 4 with respect to access concludes on the existence of three levels of in relation to student agency on LA in HEIs:

– *Level 1:* students have a right to easily access and see the LA dataset that HEIs keep about them

– *Level 2:* students have the right to rectification of (personal) data held about themselves
– *Level 3:* students have an active role as collaborators and co-interpreters.

Each level has as prerequisite the previous one. That is, students having an active role as collaborators and co-interpreters presupposes that students have easy access to the LA dataset that HEI keeps of about them (which corresponds to level 1) and that they have the right to correct data in this dataset (which corresponds to level 2). At level 2, one could further distinguish between (sensitive) personal student data and data related to students' academic achievement. The latter touches upon the question: do the students have the right to change any data related to their academic achievement with which they do not agree? This is a controversial question, especially since it encourages student agency and addresses the asymmetric power relationship between the student and the HEI. At the same time, the majority of the policies recognise (either by stating it directly or by implying it indirectly otherwise) that LA data does not give a complete picture of a student's learning. This is an important point taking into account that some researchers have expressed skepticism on the power of LA to articulate students' academic achievement and learning progress – see for example Wilson et al. (2017). Consequently, this chapter is a call for implementing LA policies in HEIs that strive for level 3 with respect to student autonomy. This could favor the idea of using LA as a means to promote honest and constructive dialogue between the tutor and the students on the students' academic achievement (or on the opposite, on the students' failure).

Other ensuing recommendations that stem from the recognition that LA data do not provide a complete picture of student's academic achievement are (1) to think critically on the power of LA to gauge deep learning, (2) to use them complementary with other methods, and (3) to avoid using them as a means of formal student assessment. These recommendations could partially counteract the presence of biases, which is raised in all frameworks presented in Sect. 11.4 and stands out as one of the most important ethical issues on LA in HE. Especially with respect to combatting biases, additional measures suggested by the policies involve continuously assessing the potential of bias in all LA activities and mitigating the effects of biases via "data minimization" e.g. tutors should not have access to students demographics; something that could have a positive impact also on data privacy.

With respect to privacy, in addition to the data minimization technique, the de-identification of data is one of the main measures suggested in the frameworks examined herein. Taking into account that the definition of privacy touches upon access of LA datasets to those identified by the institution as having a legitimate need to view the datasets, it can be concluded that at some extent privacy is inevitably interwoven with access, something that might complicate the study of the frameworks. It is worth noting that some of the universities included in this study did not have in place a comprehensive privacy policy specifically dedicated to LA. Yet, they explicitly stated that the use of LA follows the wider policy of the university on student data (which was quite comprehensive). Something that generates the question whether a dedicated privacy LA policy is actually needed taking into account that the wider privacy policy of the university provides among others recommendations on what constitutes a legitimate need to access and view student data. Yet, student agency could be an answer to what makes a LA privacy policy unique. Similarly, to the concept of access, privacy was ope-rationalised in different levels with respect to student agency in the selected frameworks, ranging from student privacy coupled with access rights and restrictions imposed by the HEIs to privacy self-management on behalf of the students.

Finally, a recommendation that emerges is to promote training of all stakeholders and professional development of tutors to optimise the use of LA in HEIs, something that has been suggested in some of the selected policies. This recommendation could also be viewed as part of a wider and more holistic approach to exploit LA as a means to promote the Scholarship of Teaching and Learning in technology-enhanced learning. That can be crucial in the current post-COVID19 digital era. Yet, there is a fine line between tutor's professional development and tutor's accountability. Since it emerges that LA do not provide a complete picture of the student and that multiple interpretations of LA can be equally valid, the view of the author is that LA should not be used as a part of an accountability system in HEIs.

This chapter would not have been possible if the universities listed herein had not published their LA policies freely available online. The author joins the voices of Tsai and Gasevic (2017) who encouraged all HEIs to follow that example that promotes opportunities for widening the discussion in the research community and for sustaining the quality of the LA policies in HEIs. Limitations of this work include that it was not clear whether the HEIs selected have more detailed or updated versions of their policies available only for internal usage (Tsai & Gasevic, 2017). Also, that the number of the selected HEIs is rather small and by no means representative of the current situation as a whole. Yet, the purpose of the paper was not to judge how HEIs respond to LA ethical issues as a whole, but to highlight the main challenges described both in the literature and in the selected policies as well as the proposed measures found in the selected policies to address them. The contents of this chapter could be useful to those HEIs that wish to embark in a LA policy, as well as to researchers that study the topic of ethics in LA in HE.

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