14

LEARNING ANALYTICS AND SOCIETAL CHALLENGES

Capturing value for education and learning

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Introduction

This chapter considers both the possibilities and problematic aspects of learning analytics (LA) as a method and tool to be used to improve students' conditions of learning in education. We consider two societal developments which catalysed the field of LA. First, at the societal level, the notion of a critical citizen has been raised in relation to supporting democratic systems to hold high values and trust in institutions and governance (e.g., Norris 2011). The notion implies that societies need knowledgeable and scrutinising citizens for democratic improvements and institutional accountability (Ziemes et al., 2020). Higher education (HE) especially has a central role in ensuring that the graduates have relevant knowledge and competencies. For instance, professional teamwork has taken a major shift from disciplinary to interdisciplinary teams to respond to the growing complexity and dynamic nature of tasks and to seek better ways to tackle ambiguous challenges (e.g., Benoliel and Somech, 2015) in sustainable and ethical ways. Considering that societal challenges demand students who are well equipped for a quickly changing world, students need, increasingly, to be able to collaborate and self-regulate and be ready to reskill and monitor their learning trajectories. Progressively, new technologies and LA tools offer potential for learners to collaborate and monitor activities and learning through tools which visualise learning processes and outcomes, thereby supporting students to achieve these goals.

The second development is datafication and algorithm-powered new methods for analysing and visualising data. The widening development and use of LA is seen as an example of the digitalisation and datafication of education and learning (e.g., Prinsloo, 2019 and Tsai et al., 2019). This has been

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connected to the amplification of evidence-based management with both negative (e.g., performance centricity, tools for control) and positive (e.g., data serving human decision-making, improving conditions for student learning or 'closing the loop') outcomes (Prinsloo, 2019 and Viberg and Grönlund, 2021).

In this chapter, we first introduce LA and how it is generating benefits for learning, taking three examples from HE as concrete cases. Second, we review the central principles of ethics, transparency, accountability, as well as skills and privacy in LA, especially from a wider perspective of uptake in society. Finally, we present conclusions on methodological challenges associated with measuring the impact of LA.

The value of LA for education and learning

LA is an interdisciplinary field with a common objective to support students, teachers, and institutions in their various tasks and roles. LA is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long and Siemens, 2011, p. 34). New technologies and LA tools offer potential for learners to collaborate, monitor activities and learning as well as support decision-making through, for example, modelling of student learning behaviours and visualisations of data for increased awareness. These include automated tools facilitating assessment of learning and development, awareness, and interaction through new functionalities and connectivity (Lim et al., 2021). This ties into the changed focus on skills such as collaboration and self-regulated learning (SRL) mentioned in the introduction.

LA support for timely and formative interventions has emerged based on technology-enabled types and modes of activities and the capturing of behaviours through data logs and visualisation (e.g., Amarasinghe et al., 2020). Other research on LA in HE has offered support for learning and teaching by using LA tools, for instance, as automated tools for SRL (Matcha et al., 2019) and multimodal visualisation of collaborative problem-solving (Vujovij et al., 2020). Further, for collaboration, LA dashboards can provide teachers and students with visualisations of the frequency of interaction, type of contributions, and types of feedback in online discussion forums (Valle et al., 2021). Customised, interactive, intelligent dashboards can offer such information in real time to help students understand the value of their own contribution and aspects that need to be improved in terms of content, formulation, or frequency of actions (Aguilar et al., 2021). In turn, this can assist students to improve their academic performance and teachers to devise pedagogical interventions for students with different backgrounds, fostering equality and inclusion (Lim et al., 2021).

LA differentiates from other data-intensive fields, for example, data mining or business intelligence, in that a driving aim is to close the loop for the benefit of the data generator such as the learner (Clow, 2012). This loop is formed of four steps: (1) learners (2) generate data, which are used (3) to produce metrics or visualisations that are used to produce insights. The last step is (4) implementation of interventions that are informed by the produced insights and are aimed at the data generator (i.e., learner). The actionable data are expected to create cognitive, administrative, and effective support (Slade and Prinsloo, 2013) and goals for improvement for learners, teachers, and other educational affected parties.

The framework proposed by Drachsler and Greller (2012) illustrates six central dimensions of LA (Figure 14.1). These dimensions offer points of departure for how to design LA tools to ensure appropriate exploitation of LA in an educationally meaningful and effective way. First, *stakeholders* are the contributors and beneficiaries as data clients and data subjects. Data clients are expected to act upon the outcome (e.g., teachers as users of teacher-facing LA tools). Data subjects are the generators of data through digital traces of activities (e.g., learners). These roles can also be combined, as in students as users of student-facing LA tools. Second, *objective*s for the use of LA in the educational setting are described in the framework as reflection and

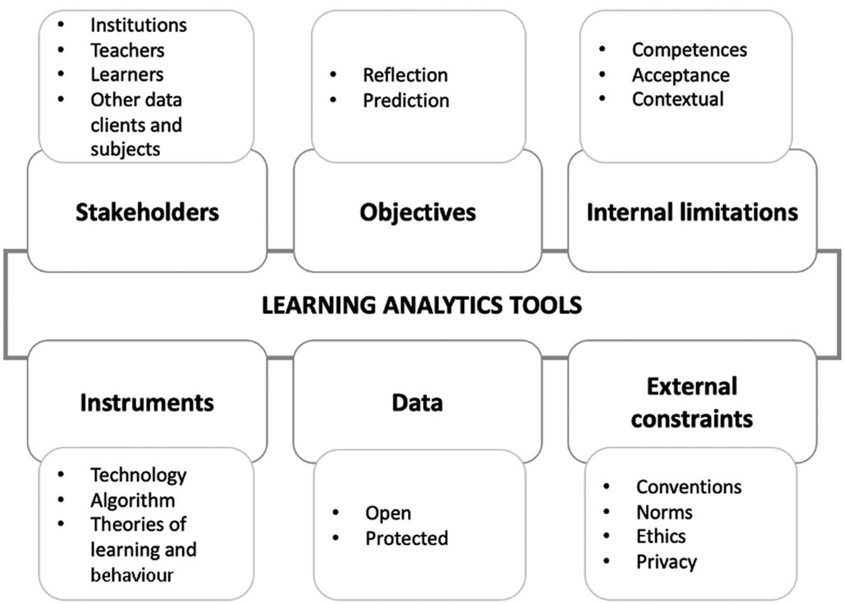


FIGURE 14.1 Six central dimensions of LA. (adapted from Drachsler and Greller, 2012).

prediction. Reflection and prediction are afforded by different visualisations and representations of learning activities or outcomes available in an analytic user interface, such as a student-facing or teacher-facing dashboard. Third, a key dimension is the *data* available, which is shared and used by the LA tools. The data available makes a great impact on what kinds of learning activities or outcomes can be mapped and how relevant and trustworthy the dashboard visualisations can in effect be. For instance, if data are missing or biased due to differences in student population or data structure between years, the validity of or the possibility to make predictions should be critically scrutinised. Fourth, the *instruments* group various technologies, algorithms, and learning and behavioural theories that conduct and inform the analysis. This is a rather broad dimension, building on the instrumentality of both methods and theoretical constructs in defining and developing LA. Fifth, *external constraints* withhold the restrictions or potential limitations for anticipated benefits. These may stem also from ethical and privacy issues. Finally, *internal limitations*, such as user competencies to gain the benefits of LA use, cannot be overlooked, including interpretation of outcomes and recognition of biases and contextual limitations.

Examples of LA: generating benefits

The following three cases illustrate examples of proposed solutions of implementing LA for specific pedagogical or learning-related activities. We chose these three examples because they tie into the societal challenge of cultivating and teaching a wider set of skills that learners need to become critical citizens.

The LA framework (Drachsler and Greller, 2012) is employed as a common structure to present and reflect the cases from ongoing research with LA tools. The first case offers analytics about student collaboration for the teacher, the second provides analytics-informed personalised scaffolds for students' SRL, and the third exemplifies the academic path LA to support student engagement and academic advising.

Case 1: Analytics about student collaboration for the teacher

The first case concerns data collected from students (data subjects) collaborating in secondary education via a computer-supported collaborative learning (CSCL) environment (Van Leeuwen et al., 2014). The data is collected and visualised in a teacher-facing dashboard for secondary schools (data clients). A problem that teachers often face is how to effectively monitor and supervise student collaboration (Van Leeuwen et al., 2015 and Van Leeuwen and Janssen, 2019). The objective of the analytics was to enable teacher reflection on students' collaborative activity. The teacher-facing dashboard

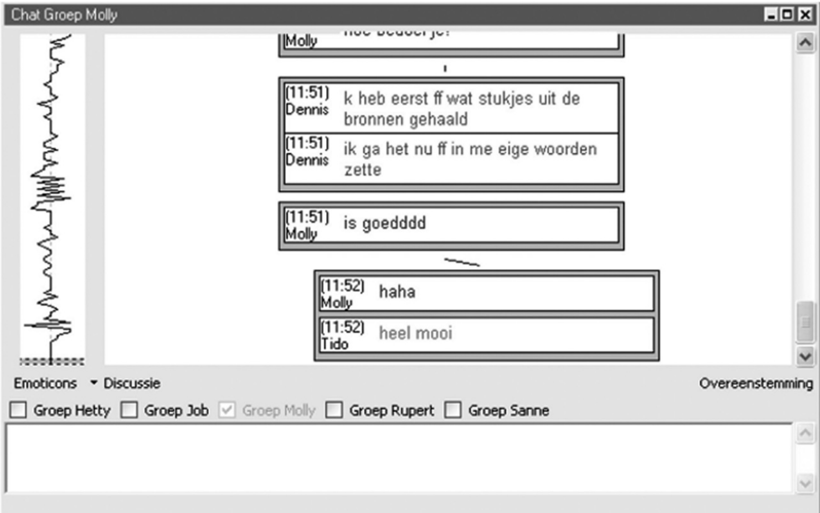


FIGURE 14.2 Chat conversation with on the left the automated discourse analysis that shows whether the group was showing agreement or disagreement in their discussion (Case 1). (adapted from Van Leeuwen et al., 2014).

offered an additional layer of information on top of the "raw" student activity of chat posts and written texts (Figure 14.2). The teacher could see this information for all groups at the same time, so the LA visualisation also has an aggregating function. It concerned a protected dataset that only the teacher and the research institute had access to. The underlying instrument in this example is the socio-cognitive assumption that constructive discussion with equal participation is beneficial for learning. Therefore, indicators derived from the data were participation rates of each student, and an automated discourse analysis of the chat conversation to determine whether each group was showing agreement or disagreement in their discussion. The teachers could therefore offer support for example when the analytics displayed unequal participation rates or when a group did not alternate between agreement and disagreement.

Case 2: Analytics-informed personalised scaffolds for self-regulated learning

The second example is related to the use of LA to support personalised scaffolding for SRL in the FLoRA project (Fan et al., 2022). Although effective SRL is associated with an increase in learning performance, learners often are not sufficiently equipped to self-regulate their learning productively

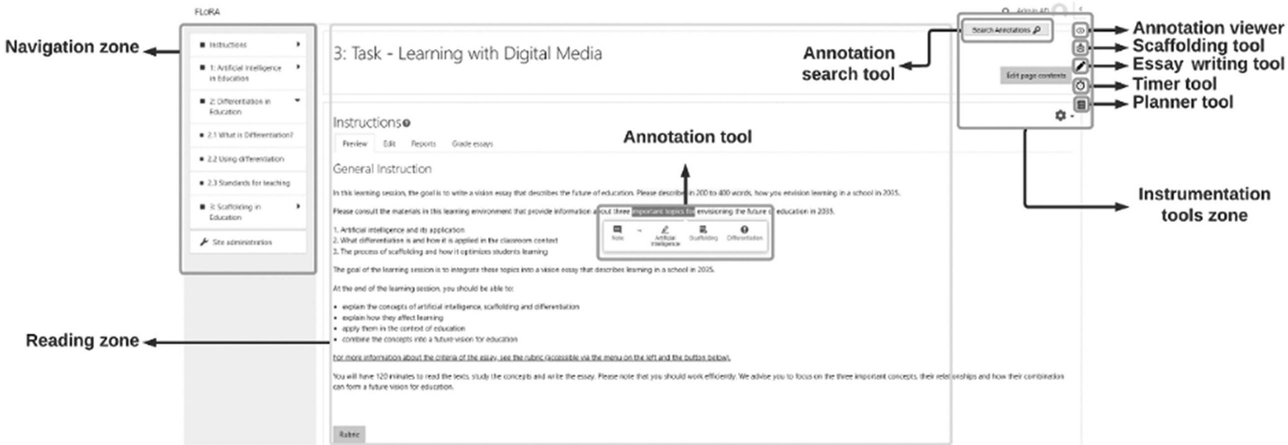
(Bjork et al., 2013). Instructional scaffolds are a proven method to guide learners and improve learning performance (Azevedo et al., 2008). However, scaffolds are usually created in a one-size-fits-all format and cannot adapt to the needs of individual students. LA holds a potential to collect data about how students regulate their learning that can be used for personalised scaffolding for SRL. The objective of LA in the FLoRA project is to improve the validity of trace data about SRL through the combination of multichannel data including navigational logs, keystrokes, mouse movements, and eye-tracking data (Fan et al., in press). Furthermore, to enhance the validity of data, additional instrumentation tools (e.g., for planning and monitoring of SRL – see Figure 14.3a) were added to the learning environment (van der Graaf et al., 2021). These data were analysed in real time to identify the occurrence of processes of SRL and to trigger personalised scaffolds at different points in time (Figure 14.3b). Empirical research showed a positive association between the use of productive strategies and personalised scaffolding (Srivastava et al., 2022).

Case 3: Academic path learning analytics to support student engagement

Case 3 presents LA designed for the purpose of supporting student engagement on an academic path in the AnalyticsAI project. Pre-service teachers' needs and expectations for LA to support student engagement (Fredricks et al., 2004 and Reeve and Tseng, 2011) on the academic path level were found to relate to four dimensions of engagement (Silvola et al., 2021): behavioural, cognitive, emotional, and agentic engagement. The academic path refers to study periods and academic years, structured according to a given degree program in HE. Students' data from study registry (data subjects) is visualised both on student and academic advisor dashboards (data clients) with the objective of fostering reflection and interaction around counselling as well as generating actionable feedback (see Figure 14.4). Student data is displayed in visualisations based on register data and made available personally to a student and the academic advisor of a group of c. 10–20 students in their degree program. The data is structured according to a student's personal study plan. Courses and credit distribution through time and study progress (completed and not completed courses) were experienced by students as the most useful feedback for goal setting and creation/revision of the study plan as well as monitoring of own progress (Gedrimiene et al., 2021).

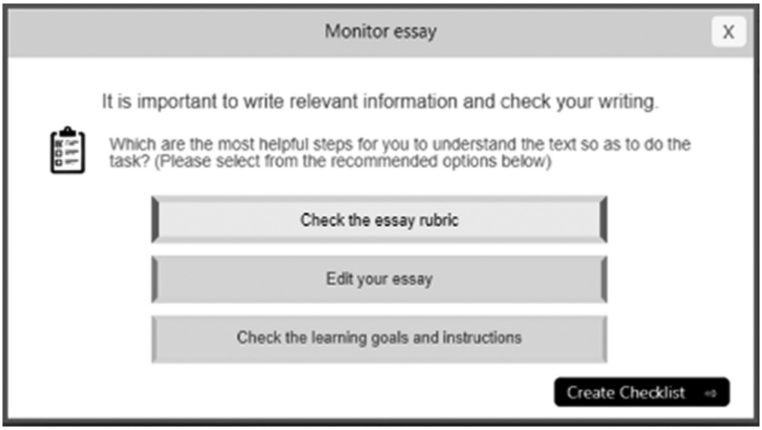
Reflection on the cases

These cases are targeting distinctly different time frames, i.e., collaboration activity, real-time analysis of processes of SRL, and monitoring of personal study plans. The cases are also designed for different data clients, supporting



(a)

FIGURE 14.3 User interface of the FLoRA environment: (a) zones of user interface and instrumentation tools.



(b)

FIGURE 14.3 (Continued) (b) an example of analytics-based scaffold that is directed at learners.

teachers to effectively monitor and supervise student collaboration, triggering personalised scaffolds for students at different points in time, and students' and academic advisors' monitoring, planning, and interaction. The three cases show how LA may be used to examine the processes and various aspects of skills development, making the processes visible, available for reflection, and recommended to engage with. Methodological choices are very central in terms of both generating the benefits but also for keeping the perimeters related to high standards in ethics, transparency, accountability, and privacy simultaneously on the table (e.g., Ferguson, 2019). This demanding interplay is likely to trigger new methodological developments, as the validity of the LA tools needs to be demonstrated. This could entail investing in multiple data modalities, and multiple time trajectories being integrated into theory-informed indicators of learning processes and outcomes. Steps in that direction that aim to improve the validity of the measurement of SRL through multiple data streams are addressed in Case 2 (Fan et al., in press).

An important question is how the added value and generated benefits are evidenced. One way to approach this is that benefits can be directly linked to the introduction and continued use of some tools, assessment methods, or feedback loops in a classroom or institution. LA tool functionalities may be specifically targeted at enhancing some skills, for example, SRL or knowledge, like specific content and procedural knowledge to be mastered in mathematics (cf., Azevedo and Gašević, 2019). Such information about skills and content learning (and typical challenges) can be fed back to various users at an aggregated level, taking notice of access and protection of privacy in

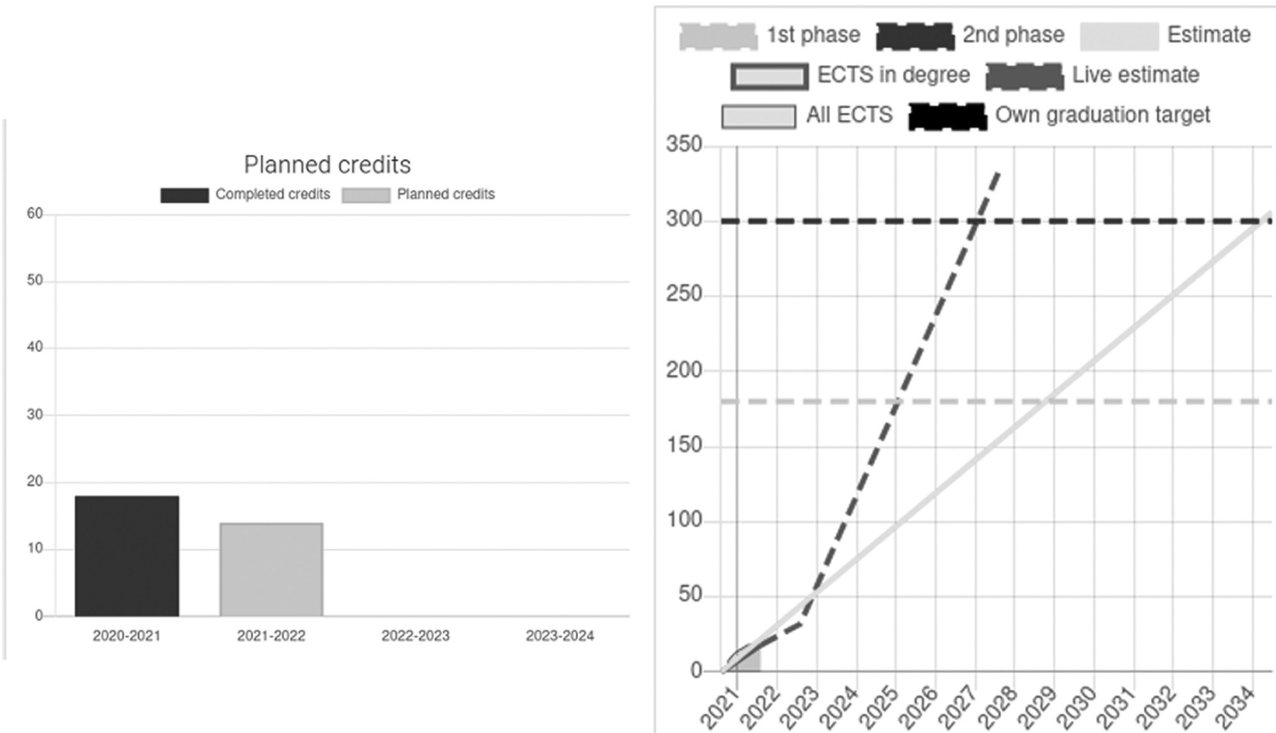


FIGURE 14.4 Visualisations to support planning and monitoring of academic path–level engagement (Case 3). (adapted from Gedrimiene et al., 2021).

different user roles. This information has various stakeholders as, for instance, with the PISA tests, you are informing policy-makers, but with (real-time) LA, you can inform the students, teachers, and schools.

However, sometimes the benefits are more indirect, offering data or visualisations for reflection, redesign of teaching (e.g., Kauppi et al., 2020) or curriculum development. For instance, in Case 3, the presentation of information in comparison with peers was controversially evaluated, as some students and advisors preferred not to have comparisons directly visible, only on demand. Some advisors suggested that the supportive interaction of the advising sessions might be jeopardised if the visualisations take all attention. This could be understood in terms of balancing between an effectiveness expectation and advisor judgements about what is educationally desirable and primary in these advising sessions. Overall, however, the advisors perceived that the dashboard provided a quick view of the students' situation and aided the identification of support needs in discussion with a student.

To conclude this section, we have shown several example cases that each show (initial) positive results of LA in education. However, there are also challenges involved, which we turn to in the next section.

Ethics, transparency, accountability, and skills to uphold ownership and privacy

Ethics

Ethical issues have a critical role when implementing new LA solutions. Especially in educational institutions, where students are in a vulnerable role compared to other institutional stakeholders such as teachers or institutional leaders (Slade and Prinsloo, 2013; see also Sarazin et al., this edition). Ethical concerns can be related to legal and practical issues, ethical decision-making, and the values behind the design and use of LA tools (West et al., 2016). Furthermore, for using algorithmic-based tools, such as prediction or automated analysis, there is yet an increased demand for ethical awareness about transparency for the actual end-users. These ethical questions involve the design and implementation of the tools and data analytic processes, quality and purposes of data traces used, capacities for data literacy and interpretation of data as well as the agentic role of users in the development work (e.g., Drachsler and Greller, 2012 and Slade and Prinsloo, 2013).

Transparency

Developments in AI and machine learning create new methodological opportunities to analyse educational data in LA tools (Teasley, 2019). Many methods for analysis are already available in technological terms. However, their application in educational contexts is related to the challenges of acquiring bias-free, relevant, and quality data as well as ensuring transparent algorithms and their interpretability (Ferguson, 2019). When addressing educational and personal data, humans are needed to give support to training AI algorithms following model interaction testing (such as uncertainty quantification and propagation). When returning the results of the algorithm in the form of a visualisation or feedback, the user should understand the results and their reliability (Khosravi et al., 2022). In the educational context, it is not yet known how to best present this to the user, how does the user work with this information, how to involve students, teachers, and learning designers in assisting to train models, and what kinds of risks or significant knowledge requirements are involved.

An important question for the field, and for society, is the fairness of algorithms. Any predicting model implies the danger of bias. In LA, a bias reflects prejudice for or against individuals or groups in ways considered unfair (Hakami and Hernández-Leo, 2020). As Gardner et al. (2019) concluded, models which ignore the differential impact of their predictions on different groups of individuals, for example, those of different genders or ethnicities, may generate undesirable properties reinforcing inequalities across groups.

Algorithms may help to determine that a bias exists in the data, therefore it can be useful for detecting biases, whereby the bias can be addressed. LA can be used to follow and measure whether the actions against bias are effective (Gardner et al., 2019 and Sha et al., 2022). However, a bias may exist also in the algorithm. Gardner et al. (2019) reported on a methodology in which model performance is evaluated across different dimensions or categories of the data. Such methodological developments are important for deeper evaluation of model fairness and progress towards non-discriminatory student models for diverse student populations.

A societal challenge relates to the moral dilemmas present with algorithms and prediction. One dilemma is related to using descriptors of the past to predict the future (see Reimann, 2016). It calls for active efforts to reveal and detect biases and acting to resolve those biases. Other moral dilemmas are also present, for example, is there an obligation to react to problems unveiled by the data in LA tools (Ferguson, 2019)? Is there leadership support to initiate actions on transparency problems towards changing practices (Tsai et al., 2019)?

Accountability

Accountability withholds central questions for the use of LA. At the institutional level, it sets the expectation that institutions have mechanisms in place to protect personal information (e.g., Hoel et al., 2017), including data collection, storage, processing, and use. Institutions need to be explicit about who is responsible for monitoring the implementation and impacts of LA use for the benefit of learning and teaching. On the other hand, students may choose not to display their data, but that may deprive them of beneficial interventions. Therefore, the nature of inclusive practices for LA is central (e.g., Pantić and Florian, 2015).

Automation of education is currently being strongly pushed into educational strategies in high-tech societies, starting with for example intelligent tutors, automated guidance for pre-admissions, or large-scale assessment. Selwyn et al. (2023) underline that the presumptions and promises of these automations need to be thoroughly examined. They argue further that technology is often "sold to educators, students and parents under the pretext of increased reliability, efficiency, or plain-old convenience" (p. 2) and in a similar vein to institutional leadership and other educational authorities with the increases in standardisation and regulation. They voice a concern that educators are expected to just adjust their actions around "what the machine is capable of recognising" (Selwyn et al., 2023, p. 2) rather than considering and ensuring meaningfulness or added value to learning and teaching.

Skills to uphold ownership and privacy

When integrating data from various sources into LA tools, it is fundamental to keep a clear idea of who is the owner of the data and uphold the ownership and privacy of data. Regulations on data privacy and protection have been put in place internationally (e.g., GDPR), forming a backbone for institutional application. To benefit from existing data, educational stakeholders must have a set of skills to cope with the digital transition (e.g., Ifenthaler and Yau, 2020; see also Seitamaa-Hakkarainen et al., this edition). These include digital, pedagogical and leadership skills to select and carry out meaningful technological changes (e.g., Damsa et al., 2021), and to adjust various roles to the new process and act upon information derived from data systems.

Transition of the use of LA from laboratory to field settings can require adjustments. Many studies have shown that analytics can provide valuable insights into SRL and even lead to positive associations with increased use of productive learning strategies (Fan et al., in press and Srivastava et al., 2022). However, classroom implementation has shown that not all types of data (e.g., eye-tracking) that are found valuable in laboratory studies, are equally usable in field settings (e.g., eye-tracking with webcams). Not only is this associated with potential privacy concerns learners may have with the intrusive nature of some data collection technologies (webcams), but it is also related to the different nature of learning process in field settings. For example, learners in laboratory studies may have an uninterrupted time working on tasks, while interruptions are frequent when working at home. In such circumstances, it becomes difficult to keep track of when webcams should be turned on and off and many learners simply decided to avoid the use of webcams at all. To avoid situations like this, LA tools for SRL should be built on the use of data that can realistically be collected by ensuring the privacy protection of learners.

Data literacy can be defined as a critical understanding of the technological infrastructure as well as strategies and tactics to manage and protect privacy, and it consists of a technological, social, and ethical dimension (Pangrazio and Sefton-Green, 2020). There is both a generic and a personal level to data literacy. The first involves individual instrumental capability to understand, interpret, and use different data, and capability for broader critical reflection. The latter involves the idea of critical reflexivity that helps individuals to think how they could utilise and repurpose the available data for their own benefit (Pangrazio and Sefton-Green, 2020 and Stornaiuolo, 2020). Combined, data literacy articulates a set of skills required to have agency in a datafied world.

To implement the results of data analysis into their teaching, instructors need to find available and suitable data drawing on alternative sources (e.g., course learning management system), evaluate its quality and trustworthiness, and handle it to obtain the information they need (Frank et al., 2016). In Case 3, the question of whether the visualisations were correctly interpreted was raised by the end-users (students and academic advisors) during the piloting feedback. The piloting showed that the users benefited from more than one guided introduction to the visualisations followed by discussions. Such discussions highlighted various perspectives, provided an opportunity to clarify interpretations of data treatment in visualisations, and supported reflection.

Conclusions

In this chapter, our aim was to outline how LA may play a role in addressing societal challenges regarding equal learning opportunities at various life stages, and in supporting students, teachers, and institutions in their various tasks and roles related to learning and teaching. We illustrated this in cases about supporting collaboration, SRL, and engagement on academic paths.

The cases presented in this chapter indicate potential benefits of LA for supporting students and teachers to develop skills such as collaboration and SRL. However, the application of LA is accompanied by potential concerns about ethics, transparency, accountability, and privacy. HE institutions are currently working on establishing policies that balance the expected benefits of the implementation of LA and these potential concerns (Tsai et al., 2019). It is the institutions' job both to offer high-quality education (which could include LA) as well as to protect the rights of staff and students concerning, for example, privacy and autonomy.

The use of digital tools has increased, partly due to the recent pandemic. Online education is likely here to stay. The review by Celik et al. (2022) on the COVID-19 pandemic time usage of LA for enhancing online education showed that the main benefits from LA tools in HE were related to monitoring, planning online learning processes, fostering learners' engagement and motivation, facilitation, assessment processes, increased interaction, and improved retention, all subject to LA tools being easy to use. The review simultaneously showed that the full potential benefits for the learners, teachers, and education are yet to be shown. For instance, enhancing collaboration by offering both students and teachers the views into moment-to-moment collaboration and skill development or offering timely support for SRL skills or needed advising at different stages of one's academic path.

Overall, there are opportunities for methodological development and research at multiple levels, ranging from tangible technology development of LA to various approaches to ensure needed competencies and equity in learning trajectories at the societal level. As suggested above, the integration of multiple data modalities and multiple time trajectories offers new avenues for methodological innovations in the analysis of learning processes. However, as the technologies become more advanced, transparency becomes harder to uphold. Sarmiento and Wise (2022) propose a call for researchers to create transparency for the process of design. This is an important step in upholding transparency for the purpose of improving the tool but also ensuring stakeholders have trust in institutional accountability on data analytics. Transparency in the process of design entails, e.g., involving stakeholders in codesign of functionality, interactively testing the tool in authentic settings, and improving ways to produce high-quality data for analysis (Ferguson, 2019; Sarmiento and Wise, 2022; and Silvola et al., 2021). A sufficiently representative stakeholder group can simultaneously inform about competence needs and ethical concerns. Thus, the adaptation of complex data analysis methodologies is critically related to keeping a human in the loop and implementing human-centred analytics (Buckingham Shum et al., 2019). Human-centredness is considered to importantly overlap machine learning-centred methods, so that the specific nature of human data and authentic learning processes are central.

There are many research questions for the future stemming from how the effectiveness and impact of LA should be evaluated or the methodological challenges associated with measuring the impact of LA. How do, for example, the moment-to-moment impressions of collaboration relate to the PISA scale of collaboration? Should LA be used for formative assessment or should we focus more on reflection-on-action (for teachers) and competence-based teaching (for students)? Likely the use of LA requires a full-scale educational innovation, and not just the introduction of a tool. Certainly, it calls for institutions to build a fundamentally stronger agenda and competencies on LA and seek guidance from learning theories and human-centred approaches for the design of LA to turn the potential to benefits of LA for supporting students and teachers.

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