Connecting Learning Analytics and Problem-Based Learning – Potentials and Challenges

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ABSTRACT

Learning analytics (LA) are a young but fast-growing field, which, according to some authors, holds big promises for education. Some claim that LA solutions can help measure and support constructivist classrooms and 21st century skills, thus creating a potential of making an alignment between LA and PBL principles and practices. Despite this argument, LA have not yet gained much interest among the Problem-Based Learning (PBL) practitioners and researchers and the possible connections between PBL and LA have not yet been properly explored. The purpose of this paper is, therefore, to investigate how LA can potentially be used to support and inform PBL practice. We do this by identifying central themes that remain constant across various orchestrations of PBL (collaboration, self-directed learning, and reflection) and present examples of LA tools and concepts that have been developed within LA and neighbouring fields (e.g. CSCL) in connection to those themes. This selection of LA solutions is later used as a basis for discussing wider potentials, challenges and recommendations for making connections between PBL and LA.

Keywords: Problem-Based Learning; Learning Analytics; Collaboration; Self-directed learning; Reflection; Self-regulation.

INTRODUCTION

Learning analytics (LA) are a field that has gained increasing attention within the wider field of educational technology but is relatively less explored specifically in relation to Problem-Based Learning (PBL). LA advocates argue that the field holds great potential for improving and optimising education, with some of them claiming that LA solutions

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can help measure and support constructivist classrooms (Blikstein & Worsley, 2016; Dietrichson, 2013) and 21st century skills (Shum & Crick, 2016). This, combined with the growing popularity of the field, makes it difficult not to consider the possibility of making a connection between LA and PBL, and start asking what LA can offer to PBL practitioners and vice versa. In this paper, we try to take a step back, look beyond the promises, and examine the field of LA to understand the potential and challenges it offers in relation to PBL by discussing both concrete tools and practices as well as recent conceptual developments.

We start with a brief presentation of the field of LA, its potential applications and reasons for its growth. Next, as PBL is a multifaceted pedagogy and field that covers a diversity of practices, theories, and models, we draw out some common and central themes (collaboration, self-directed learning and reflection) that cut across various orchestrations of PBL. We do so, as we do not want to limit our discussion to a particular implementation or model of PBL, such as the Maastricht 7-step approach, or the Aalborg PBL model. Although LA have not yet been much spoken of in connection to PBL, LA and neighbouring fields, such as CSCL, have already been looking into LA's potential in relation to some of the themes that are also of interest to the PBL community such as problem solving and collaboration (e.g. Fischer, 2015; Joksimović et al., 2016; Saqr, Fors, & Nouri, 2018). Thus, in this paper we aim to look at examples of how the central PBL themes that we identified have been addressed by the LA community and researchers from other fields, with or without a specific reference to PBL. We use the themes as a base for examining how various existing LA tools, practices, and approaches might hold interesting perspectives for PBL, but equally for reflecting on the shortcomings and challenges in relation to employing LA within the frame of PBL. We conclude the paper with a synthesising discussion and recommendations on the way forward, as the overarching purpose of the paper is to explore how LA can inform PBL and what the challenges and potentials are of employing LA to support PBL.

WHAT ARE LEARNING ANALYTICS?

LA are concerned with the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Siemens, 2010). This field of research is relatively new, as it only just emerged in the last decade, but it has roots in more mature fields, such as business intelligence, web analytics, educational data mining and recommender systems (Ferguson, 2012). Its rise was fuelled by three driving forces (Ferguson, 2012): the challenge of extracting value from a growing body of educational data collected from

online environments, significant increase in the popularity of online learning with associated need to optimise the online learning opportunities, and, finally, the political demand to show and improve performance. The data that the LA tools use to achieve different educational goals is mainly gathered through monitoring students' online activity (e.g. access to resources, logins, textual input) (Rubel & Jones, 2016). This data collection is not really limited to specific sources, such as Learning Management Systems (LMSs), but encompasses various tools, techniques or environments (García & Benlloch-Dualde, 2016), e.g. forums, blogs, interactive whiteboards, social sites, libraries, or MOOCs.

Potential applications of LA in education

The proponents of LA argue for a wide range of potential uses, such as prediction, intervention, recommendation, personalisation, reflection or iteration and benchmarking, that are connected to challenges driving the fields' development (Khalil & Ebner, 2015). The prediction of students' future performance and activities allows for identification of at-risk students (Sclater, Webb, & Danson, 2017), applying early interventions and thus achieving different stakeholders' goals, such as an increase in retention (Almutairi, Sidiropoulos, & Karypis, 2017), and improvement of students' academic success (Khalil & Ebner, 2015). LA can be used as a tool to provide different types of recommendations to students regarding people, resources, activities (Duval, 2011), or choice of courses (Ferguson et al., 2016). They also have a potential of creating more personalised learning opportunities for students either by automatically adjusting the material to individual learners or by providing students with recommendations that they can use to shape their learning (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). LA aim to provide both learners and teachers with data for reflection on their work that can lead to improvements in the learning process in the future (Khalil & Ebner, 2015). Another potential use of LA, benchmarking, can be seen as "a learning process, which identifies the best practices that produce superior results" (Khalil & Ebner, 2015, p. 131). In that sense, one of LA' goals, is finding the weak aspects of the learning processes and environments, and optimise them based on the knowledge of best practices.

The reasons for the continuous growth of the field

Even though the field of LA still faces many challenges, the promises and hopes associated with the application of LA are high, so it is not surprising that the field's popularity is increasing rapidly (Ferguson et al., 2016). Simon (2017) gives several reasons why LA will become more widespread in the near future. One of them is related to constant technological development, which ensures that the new LA tools become less dependent on data collected from online environments. Without data on students' interaction outside of the online systems, we are not able to paint a holistic picture of students' learning process (Mangaroska & Giannakos, 2018; Slade & Prinsloo, 2013).

One way in which the field has been trying to address this challenge is by putting more focus on multimodal learning analytics (MMLA), understood as "multimodal data collection and analysis techniques" (Blikstein, 2013, p. 102). Data for MMLA can be collected using not only logs of activities completed on a computer or mobile devices, but also by employing such technologies as biosensors, eye tracking, infrared imaging, or wearable cameras (Blikstein & Worsley, 2016). Such a wide range of data sources allows for use of various types of techniques that can give educators an opportunity to analyse speech, handwriting, sketches, gestures, affective states or eye gaze, which means that MMLA potentially makes it possible to analyse, measure and optimise learning happening in face-to-face settings.

Another rationale for explaining the growth of the field is associated with the economic pressure to automate education (Taylor, 2001) in order to increase the number of graduates, and improve performance while lowering the costs (Mehaffy, 2012). It is clear that there is a strong political interest in relation to how 'data' can inform and improve education (Williamson, 2017). Perhaps for that reason LA are often oriented towards individuals rather than groups or networks (Dohn, Sime, Cranmer, Ryberg, & de Laat, 2018; Fawns, 2018), and identifying at-risk students to provide them with early interventions remains the primary focus within the field (Ferguson et al., 2016). This trend is associated with LA solutions that are technology- rather than pedagogy-driven (Dohn et al., 2018), a shift that may bring worrisome consequences to education, with learners being sculpted not by pedagogic expertise, but rather by assumptions of technical experts (Williamson, 2016). While this overarching tendency needs to be acknowledged, it does not encompass the whole field of LA. There is a tension between the economic and institutional perspective concerned with dropout rates, and the more research-led trend that focuses on constructivist principles, 21st century skills, student autonomy and providing actionable feedback to improve learning rather than retention.

The increase in popularity of the field is then related also to the growing emphasis on developing students' 21st century skills (Dede, 2010). The new set of skills, including collaboration, independent thinking, problem-solving, and decision making (Silva, 2009), is needed for successful work life and citizenship, some argue (Dede, 2010). Those skills often cannot be sufficiently (or at all) measured by traditional assessment methods (Griffin & Care, 2015), with some researchers claiming that they cannot be measured at all (Silva, 2009). As the various learning-related interactions are now frequently mediated by ICT and thus create digital traces, educational researchers hope that LA will bring an opportunity for measuring and facilitating 21st century skills (Simon, 2017).

PROBLEM-BASED LEARNING

As initially stated, we do not take departure in a particular orchestration or model of PBL in this article. Rather, we aim to describe some broad and commonly shared principles that cut across various concrete implementations of PBL. Further, we do so, with the specific aim of identifying themes that have also emerged within the field of LA.

Broadly speaking, PBL is a pedagogical philosophy covering a multitude of practices and is applied differently whether implemented in K12 or Higher Education. Even within higher education, there are different PBL models, such as the Aalborg PBL model (Kolmos, Fink, & Krogh, 2004) and the Maastricht model (Graaff & Kolmos, 2003). In PBL-based models, learners usually have a high degree of autonomy and responsibility for their own and others learning, and PBL often encompasses elements of reflection, peer- and self-assessment (Graaff & Kolmos, 2003; Savery, 2006; Savin-Baden, 2007). Generally, various models of PBL feature group work or collaborative work, although the exact nature and extension of the collaborative work can differ (Ryberg, Koottatep, Pengchai, & Dirckinck-Holmfeld, 2006). Savery (2006) crystallises a number of PBL principles to the following three:

> 1) *the role of the tutor as a facilitator of learning, 2) the responsibilities of the learners to be self-directed and self-regulated in their learning, and 3) the essential elements in the design of ill-structured instructional problems as the driving force for inquiry.* (Savery, 2006, p. 15)

Savery (2006), it should be noted, equally stresses collaboration as an essential feature, although he does not mention it in the summary of the principles. However, the distribution of responsibility for the learning process clearly rests with the students, with the 'teacher' as a facilitator, and the notions of autonomy, self-directedness or self-regulation as central. Adding to this, the notion of ill-structured problems as the driving force for learning is a very central aspect of PBL, which however is difficult to find directly addressed in the literature of LA.

In this paper, we contribute to examining the issue of making an explicit connection between LA and PBL by picking out three central themes within PBL, that also align well with research within the field of LA, namely: collaboration, self-directed learning, and reflection, which are central PBL themes also highlighted by Camacho, Skov, Jonasen, & Ryberg (2018), and we investigate how these themes have been addressed by the field of LA and neighbouring fields.

LEARNING ANALYTICS TO SUPPORT PROBLEM-BASED LEARNING PRINCPLES – CONNECTING PBL AND LA

The field of LA is still in the process of establishing the connections to the learning theories and educational research, with many of the existing tools not naming the theory or paradigms of learning they are based on. Thus, it is not surprising that the number of LA applications that specify their relation to PBL, or any other learning approach, is still limited. As of now, there is no agreed upon existing set of LA tools that can successfully support PBL. The majority of the LA tools that are available in LMSs do not provide very diverse information on students' activities, focusing mainly on system logs and clicking behaviour (Dietrichson, 2013), and using only one platform for data collection. Mangaroska & Giannakos (2018, p. 12) argue that this limitation "hinders the holistic approach to understand the learning process as an ecosystem". The existing LA tools and plugins for LMS are seldom mentioned in LA literature in relation to supporting and analysing 21st century skills, and, with rare examples (Triantafyllou, Xylakis, Nilsson, & Timcenko, 2018; Triantafyllou, Xylakis, Zotou, Tambouris, & Tarabanis, 2018), are not really utilised by PBL practitioners. Despite these limitations, PBL practitioners may soon find themselves in a situation where using LA features is not a possibility, but a requirement. As the popularity of the field of LA is growing, with new LA tools being introduced into existing LMS and the institutional need of showing performance, there is a pressure to start introducing LA into the teaching practice at different levels of education. We therefore find it valuable to put more focus on the discussion of the possible connections between LA and PBL and to involve PBL practitioners in this discussion. We start by briefly describing two examples of LA research related specifically to PBL. This will be followed by examples of existing LA features that do not have an explicitly stated connection to PBL, but still investigat or support some of the main principles of PBL: collaboration, self-directed learning, and reflection (Camacho et al., 2018).

Hogaboam et al. (2016) conducted a study which aimed to investigate the use of LA tools to support instructors in facilitating an online PBL workshop for medical students. The facilitators in the study were given access to the students' part of the learning environment, including a video feed, discussion space, and a whiteboard section. Moreover, they could consult different visualisations that were made available for them in a LA dashboard, such as charts showing the students' textual output in relation to others, the textual output produced by the group as compared to other groups, and a progression bar representing task completion. The dashboard also included a scrollable news feed showing a list of the actions performed by the students, an interaction graph of the discussion, and a word cloud consisting of the most commonly used words. However, even though a variety of LA features were created to support facilitation, the actual use

of the LA dashboard turned out to be very limited, as the facilitators did not really know how to make sense of the visualisations. Instead, they based their facilitating actions on the output created by students.

The PBL workshop enriched with the LA dashboard analysed by Hogaboam et al. (2016) happened entirely online, which made the data collection significantly easier than if it took place in a face-to-face or hybrid setting. An example of a research that aimed to analyse data collected in a face-to-face context is the work of Spikol, Ruffaldi, & Cukurova (2017), who attempted to analyse which of several multimodal features could be considered good predictors for collaborative problem solving (CPS), a process common within Problem-Based and Project-Based Learning. The engineering students worked in groups, using furniture supplemented with MMLA system capable of tracking the position of faces, hands and other objects, and a platform capturing interaction information. Spikol et al. (2017) coded video-recordings of the group work, to later compute scores on different indicators of successful collaborative learning, such as physical engagement or synchronisation. They managed to show that the direction of students' gaze, the distance between them, and hand motions are regressors of the above indicators, and could be used to identify collaboration. The authors argue that those results show that MMLA could support an assessment of CPS within Project-Based Learning and provide insights into the processes involved in face-to-face learning.

Collaboration
One of the recent proposals focusing on collaboration was made by Koh, Shibani, Tan, & Hong (2016) presenting a LA system based on an explicit pedagogical model, called the Team and Self Diagnostic Learning Framework (TSDL). Their LA solution is, so far, not based on analysing Big Data on students' actions, which distinguishes it from other proposals within the field. In their team competency awareness program, Koh et al. (2016) decided to utilise existing surveys from social sciences and represent their results in a visual form. Those so-called dispositional analytics (Shum & Crick, 2012) were used to guide students in reflecting upon their team collaboration in order to build self and team awareness. The 14-years-old students worked in groups on collaborative inquiry tasks and were afterward asked to fill in an online survey based on teamwork competency dimensions. The results of the survey were then represented on a radar chart showing a micro-profile of teamwork competency of an individual, according to both himself and his peers. In the next step, the students were asked a range of questions designed to help them make sense of the data and how it could be used to improve the group performance. Both students and teachers were generally positive about the experience, with students saying that it supported them in gaining a better understanding of how well they did in teamwork and how they were perceived by others. The main challenge reported by Koh

et al. (2016) was related to finding time in the busy school schedule when the students could participate in the sensemaking part of the framework.

When it comes to LA features aimed for the tutors rather than students, probably the most common role of the analytics is providing tutors with information needed for various interventions (Herder et al., 2018; Lonn, Krumm, Waddington, & Teasley, 2012; van Leeuwen, Janssen, Erkens, & Brekelmans, 2014). Herder et al. (2018) aimed at creating a tool to support teachers' interventions in a virtual internships systems. The Process Tab tool was meant to represent and visualise the discussion of both groups and individuals. Teachers were given access to a 'summary view' showing the quality of the contributions made by individuals, network models, but also suggested interventions. The LA features were updated in real time, so the teachers could at any time during class access the system and see who needed support. However, even though the teachers saw the potential of using the tool, they did not really utilise it, as they were not able to find time to consult the LA features during the busy classes. Moreover, even though the tool was analysing contributions to discussions, it seems that the focus were individual contributions rather than the group-level analysis.

Another example of a learning analytics tool to support teachers' diagnosis and intervention, was suggested by van Leeuwen (2014). The experimental study utilised learning data collected on student activities in past courses. The teachers in the control group had access to all of the students' activities that had taken place in a chat tool and a shared text editor. The experimental group had the option of using two additional features, a pie chart with the relative contribution made by the group members, and a visualisation of the group's level of agreement/disagreement based on the content of the chat tool. The teachers were presented with vignettes showing collaborative situations representative of groups with different problems. They were asked to rate each group's participation and discussion and had an option of sending an intervention message. The results showed that the teachers who had access to LA features were able to give more details when explaining the score that they assigned to the groups, were more successful in spotting the participatory problems in collaboration and intervened more frequently. Interestingly, the visualisation of group's disagreement had an unclear effect, with teachers in experimental conditions not being able to point out the groups that showed signs of discussion problems. While some of those results are promising, the study was run using data from the past, and thus did not investigate how the fact that the teachers had access to the analytics influenced the learning experience of the students.

Forums are one of the most commonly used collaborative online tools (Bakharia & Dawson, 2011) that in majority of LMSs are analysed only on a very basic level. However, there is a significant body of research (de Laat, Lally, Lipponen, & Simons,

2007; Luhrs & McAnally-Salas, 2016; Romero, López, Luna, & Ventura, 2013; Suraj & Roshni, 2015), focused on investigating forum interaction and participation using social network analysis (SNA). One of the examples is The Social Networks Adapting Pedagogical Practice (SNAPP), a tool which offers a real-time SNA using various algorithms in order to support teachers in finding and understanding the different network structures (Bakharia & Dawson, 2011). Among other functionalities, SNAPP provides interactive visualisations of the network and helps the forum facilitators in locating isolated students, identifying and acting upon network patterns (e.g. facilitator-centric pattern), or discovering the emergence of sub-groups and cliques.

Rabbany, Takaffoli & Zaïane (2012) propose another LA tool utilising SNA, called Meerkat-ED. This toolbox builds two types of networks, one of them concerned with the interaction between students (social network of students) and the other one that provides a hierarchical visualisation of topics (network of phrases). Rabbany et al. (2012) argue that this additional feature allows the teacher to see which topics were addressed in the discussion, which students participated in those topics, and how active they were. The case study showed that the teachers found Meerkat-ED to be a valuable tool that allowed them to get an overview of the students' participation in the forum, and identify both the influential students, as well as, the lurkers.

An interesting implementation of LA for collaboration, AMOEBA, was proposed by Berland, Davis, & Smith (2015). The function of the tool was to support the teachers in pairing the novice programmers at the middle school and high school level to best facilitate collaboration. The system runs a real-time analysis of the progress that students are making in their programming tasks, tracks which students work in a similar manner, and based on that provides the teacher with recommendations on how to pair students to improve learning. Berland et al. (2015) showed results according to which the students whose teams were created with help of AMOEBA improved in terms of their code's complexity and depth.

Self-directed learning
Self-direction is a quality of learners who take initiative and responsibility for their own learning (Hiemstra, 1999). Self-directed learning (SDL) and self-regulated learning (SRL) are terms that are often confused or used interchangeably (Gandomkar & Sandars, 2018). While the two concepts share some similarities, there are certain differences between them. Gandomkar & Sandars (2018) explain that while SDL can be seen more as an approach to learning that a learner can take up and follow, SRL is a strategic and dynamic process that a learner utilises to ensure that she achieves her learning goals. As successful SDL must first be successful SRL, we decided to include examples of LA solutions that directly mention either SDL or SRL.

Dawson, Macfadyen, Risko, & Foulsham (2012) proposed the use of The Collaborative Lecture Annotation System (CLAS) in order to encourage self-directed learning among students. CLAS is a video annotation tool that allows the students to annotate important points in a video, share their annotations and review annotations made by others. The access to their own annotations combined with the ability to compare with peers helps the students to reflect on the significance of different points in the video and supports the instructors in checking whether the students recognised the important concepts. Dawson et al. (2012) argue that the tool helps students to develop their self-monitoring and self-management skills thus assisting them in being self-directed learners. Risko, Foulsham, Dawson, & Kingstone (2013) ran a user experience study of CLAS and reported that students found it useful to have access to the group graph that helped them find important information in the video and considered the annotation tool easy to learn. While the proposed tool was interesting, it was not reported whether it actually succeeded in encouraging self-directed learning by increasing motivation, supporting self-monitoring and self-management.

Analytics for Everyday Learning (AFEL) project attempts to address the issue of collecting and combining data from different sources and platforms (Holtz et al., 2017). Among its expected outcomes is a set of tools that would allow users to track their online learning activities in order to support self-directed learning. Holtz et al. (2017) describe a browser extension that extracts search history, which is later analysed to derive topics that are divided into clusters to obtain a set of broader themes. The data from this analysis is then fed to an interactive dashboard with several visualisations that students can adjust to their needs, including an overview of the larger themes, together with information on the relative number of learning activities associated with each topic. Another feature allows the user to track their learning intensity and progress, in relation either to specific topics or all of their learning activity. The dashboard also provides resource recommendation based on students' learning situation. The AFEL tools are still at an early stage of development, so they not only need further work but also lack feedback from users, which means that their positive influence on self-directed learning capabilities has not yet been shown.

Tabuenca, Kalz, Drachsler, & Specht (2015) conducted a study that explored the effects that regular tracking of the time spent on learning activities has on self-regulated learning. The authors provided the students with two tracking tools: an Android app and a multiplatform web interface, combined with SMS notifications. The results of the study showed that logging time spent on studying might lead to an improvement of time management skills and time planning, as assessed through questionnaires on self-regulation. The time of the notifications mattered, with randomly timed notifications having no positive influence on time management, and fixed-time notifications showing

a potential of improving time management skills. The influence of tracking on learning varied depending on the tracking option used, partly because participants using the mobile app tended to be more consistent and regular in their logging. Tabuenca et al. (2015) also showed that notifications including personal LA influence time management slightly more positively than notifications that consisted solely of generic tips regarding self-regulation. Interestingly, the authors reported a lack of correlation between the number of time logs, the duration of the logged time slots, and grades obtained by the participants.

One of the topics that Tabuenca et al. (2015) touched upon in their work is providing the students with valuable feedback in order to support their learning regulation. According to Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner (2018), the field still lacks the knowledge and guidelines in regard to the design of actionable feedback based on the learner's goals and characteristics. The existing tools often fail in increasing learners' motivation or helping them develop a mastery orientation, and do not provide support that could help students make sense of the visualisations and regulate their learning to do better. Sedrakyan et al. (2018) address those deficits by proposing a model listing the concepts recommended in relation to designing regulation-supporting feedback in LA dashboards. The model includes several design implications concerning different aspects of the design of dashboards, such as the need for the environment to give students a possibility of having a planning profile, understood as a collection of different features that allow for setting sub-goals, creating learning plan, assigning resources, and allocating time. The dashboard environment should also support the students in monitoring their goals to help them adjust their plans and strategies and provide information on whether students' adaptation to certain challenges was successful. Some other recommendations include the need to give students and teachers control over aspects of the feedback they receive, and to offer both cognitive and behavioural types of feedback.

Reflection
LA tools aimed at supporting reflection often focus on analysing and facilitating reflective writing. It has been agreed throughout educational research that reflective writing is a process important for effective reflective practice, activating students and increasing engagement (Bolton, 2005; Thorpe, 2004; Towndrow, Ling, & Venthan, 2008). However, its use in education is challenged and limited by the time-consuming process of assessment and providing feedback. Currently, the contents of students' reflections are more often than not analysed manually, making it challenging to include reflective writing in courses where the ratio of teachers to students is low. It is not uncommon for facilitators in different PBL implementations to be responsible for guiding a high number of students. In some cases, one tutor may be responsible for facilitation in a classroom consisting of a few hundred students (Nicholl & Lou, 2012). Here the answer could be designing learning analytics for an automatic detection (Ullmann, Fridolin, & Scott,

2012) and assessment of reflection, combined with automatic actionable feedback (Gibson et al., 2017).

One of the main challenges that come with providing feedback is the analysis and assessment of reflective texts. While reflection is not really a new concept in education (Ullmann et al., 2012), the methods for assessment of reflective writing are still a work in progress and not yet fully established. This means that researchers who aim to design LA for reflective writing need to first adapt existing or develop a new assessment method/framework to be used for their tool (Gibson et al., 2017; Kovanović et al., 2018). Before reflective text can be assessed and feedback can be provided, it is first necessary to detect reflection in written text, which is in itself a challenging task, at least partly due to the lack of a large corpus consisting of reflective texts that could be used to refine the machine learning algorithms (Ullmann et al., 2012).

Ullmann et al. (2012) ran a study in which they developed a tool for automatic detection of reflection and made a comparison between the work of the automated systems and human ratings given access to the same texts. In the study, a framework based on five different elements of reflection was used to distinguish between reflective and non-reflective texts: description of an experience, personal experience, critical analysis, taking perspectives into account, and outcome of the reflective writing. A set of indicators together with rules were developed to locate the elements of reflection. The text was considered reflective if a certain number of indicators for each of the reflection elements was found within it. The results showed that the texts automatically categorised as reflective were also rated higher in terms of the quality of reflection by the human raters, which is promising for the further development of automated systems recognising and assessing reflective texts.

Gibson et al. (2017) report on the developments made by Authentic Assessment Analytics for Reflection (A3R) research project, which aimed to not only analyse the reflective texts but also to investigate the potential of providing automatic feedback that could inspire students to undertake actions that could improve their reflective writing. The project utilised and further developed an existing platform AWA (Academic Writing Analytics). Gibson et al. (2017) proposed a new conceptual framework for reflective writing, consisting of three moves (context, challenge, change), a modifier based on whether the students linked any of the moves to themselves, and three expression types (emotive, epistemic, critique). The text was annotated, with comments on paragraphs supplied in the margins, and expressions marked with symbols representing different elements of the described framework. The feedback was context-independent and not very detailed. Many of the students considered the feedback given to them helpful for their reflective writing and liked being able to see where improvement was needed. However, some

participants wished to be given more information on how to improve and felt that the comments were not clear enough. The evidence of action was limited, though the students who did modify their drafts, showed improvement in the quality of reflection. Gibson et al. (2017) discuss the need of including the contextual feedback that would also allow for providing more details and making the feedback more understandable.

DISCUSSION

At a first glance, the relationship between PBL and LA appears ambiguous. On one hand, Wilson, Watson, Thompson, Drew, & Doyle (2017) point to the existence of a potential conflict between the LA's goal of facilitating personalised and individualised learning, and the collaborative, social idea of learning that underpins social constructivist learning theories. On the other hand, Blikstein & Worsley (2016) argue for the contribution that MMLA can make to understanding and promoting constructivist forms of learning. The goal of this paper was to investigate the potential connection between LA and PBL. The field of LA is still young, and new solutions are constantly being developed. While not many of them specifically mention PBL, there is a significant body of research, referring to some of the PBL central themes, collaboration, self-direction, and reflection. In our work, we described and discussed representative examples of tools developed to measure, assess, and support the learning processes and skills associated with those central themes. Now we use these examples in order to examine what we can learn from them in order to help pinpoint both the possibilities and the challenges of employing LA to support PBL. We give special focus to the future research implications associated with these challenges in order to provide a foundation to move forward.

Possibilities
The examples that we described show that skills and themes associated with PBL are gaining attention from the LA community. They also represent a piece from the variety of work that has already been done and is currently being undertaken in the field of LA. Even though the described tools are often in their early stages of development and have not yet been integrated into any specific program or institution, they do show a promise of supporting both learners and facilitators in their everyday PBL practice.

Perhaps the most important role that LA can play in the PBL process is the one of supporting students in the development of their PBL-related skills. We described the examples of LA tools developed to provide students with information, usually in form of visualisations, on their collaborative skills (Koh et al., 2016), or quality of their reflective writing (Gibson et al., 2017). With use of different LA features students were able to monitor progress in different learning topics (Holtz et al., 2017), track their learning

patterns over time (Tabuenca et al., 2015), and compare their judgment with others (Dawson et al., 2012), and thus, gain the information and support needed for successful self-directed learning.

Majority of the described tools were directed to facilitators rather than students, which may be associated with the fact that it is easier to provide the facilitators with additional information rather than creating automatic actionable feedback aimed directly at students. The facilitators were presented with a variety of different tools and visualisations. The described solutions show that LA have a potential of supporting facilitator in a variety of ways, such as overseeing the collaboration between students (Herder et al., 2018; Hogaboam et al., 2016; van Leeuwen et al., 2014), providing first assessment of reflective writing (Gibson et al., 2017), or giving an overview of whether students managed to find the important information in video material (Dawson et al., 2012). Some of the ways in which data was used to support collaboration, was assigning students into groups based on their collaboration patterns (Berland et al., 2015), or identifying participation problems or arguments (van Leeuwen et al., 2014). The overview of tools shows the potential that LA have not only for assisting students but also for significantly reducing the workload of teachers. However, it is also clear that the strong focus on the facilitators, rather than the students, sits somewhat uncomfortably in a PBL context.

Challenges and implications for the future

Involving users in the design
The challenges associated with developing LA for PBL do not much differ from those that the LA field as a whole is still encountering. One of them is related to giving more attention to the supply side rather than the demand side (Ferguson et al., 2016). This means that there is a stronger focus on answering the needs at an institutional level, than on developing tools that teachers and students could use to support the teaching and learning processes. As a result, users often do not know how to make sense of the visualisations that are presented to them (Hogaboam et al., 2016), find the provided information insufficient (Gibson et al., 2017), or have difficulty integrating the tool in their existing practice, e.g. due to time constraints (Herder et al., 2018; Koh et al., 2016). Not including the perspective of students and other stakeholders in the design process is a problem that the LA field has been facing since its creation (Ferguson, 2012; 'General Call | Learning Analytics & Knowledge 2017', n.d.). Even though there is no lack of student-facing LA tools, the students are rarely actively involved in the design, and the information of how they perceive usability or usefulness of the LA system is not provided (Bodily & Verbert, 2017). This should be done in order to ensure that those tools really

answer their needs (Kilińska, Kobbelgaard, & Ryberg, 2018) and can be successfully included in the existing learning and teaching practices.

Designing a practice

The examples also provide a further base for the argument already voiced by some LA researchers (Mangaroska & Giannakos, 2018; Wise, 2014), which is that it is not enough to create LA tools. What also needs to be considered is the practice surrounding the use of those tools in regard to agreeing on the goals, assigning time, and providing guidelines for making sense of the presented information. Out of the described LA solutions, only one (Koh et al., 2016) included features for supporting the process of reflection and planning actions to be taken based on the information from LA tools.

Building a holistic picture of learning

Many of the current LMS tools do not paint a very holistic picture of the learning process as they do not collect the data from many sources, but focus e.g. only on data available LMSs. The work meant to combine data from different sources and platforms has already started (Holtz et al., 2017) but it is still in its infancy. The challenge comes from the high complexity and diversity of the learning ecosystems used by students. In many cases, e.g. within Aalborg University's PBL Model, Moodle is often used to a very limited extent, and it is up to the students to find a combination of tools that suit their learning needs (Caviglia, Dalsgaard, Davidsen, & Ryberg, 2018; Sørensen, 2018). Some educators attempt to create their own version of PBL-friendly systems, either by making one from scratch or developing plug-ins for the LMS used by their institution (Ali, Al-Dous, & Samaka, 2015). Therefore, it is important that future research focuses on understanding and mapping the learning ecosystems. What is also very promising, is further development in the area of MMLA that attempt to combine the data on online activity with face-to-face data. It must be noted, however, that building MMLA solutions faces many technical challenges (Ochoa & Worsley, 2016).

What should also be considered, is development of LA based not only on automatically logged data on students' activities, but also self-reported data, as we saw e.g. in the work of Koh et al. (2016). Some argue that the numbers alone are not enough, as what remains unknown is the intent (Ellis, Han, & Pardo, 2017), and without the knowledge of the full context, it is difficult to analyse the data. Even when the external learning conditions are the same, internal conditions may differ significantly (Gašević, Dawson, & Siemens, 2015). Combining the automatically recorded logs with self-recorded data may be a way of gaining a greater understanding of the actual learning processes (Ellis et al., 2017), but so far this solution is rarely utilised in the field of LA (Tempelaar, Rienties, & Giesbers, 2015).

Providing actionable feedback

What still requires further work is providing students, also those who already do well in the course, with actionable feedback that can help them improve their work (Sedrakyan et al., 2018). Out of the presented LA solutions, only a few aimed at giving the students automated feedback that they could later actively use (Gibson et al., 2017; Tabuenca et al., 2015), and even then, some of the students reported that they did not know how to use the information to, e.g. further develop their reflective writing skills. In order to address this and other shortcomings, the field needs to work on its connection to the learning sciences and educational research (Ferguson, 2012; Ferguson et al., 2016; Gašević et al., 2015; Mangaroska & Giannakos, 2018; Sedrakyan et al., 2018).

Establishing collaboration between PBL and LA researchers

The field of LA is working on creating stronger connections to learning sciences and educational research, but in most cases, it is not quite there yet. The main implication that seems to be coming from this fact is that if the LA solutions are to really support the PBL principles, what needs to be considered is an active collaboration between PBL practitioners and LA researchers to create tools that are rooted in the existing practice and educational knowledge of the field of PBL. This collaboration could lead to the development of further frameworks and guidelines for the design of future LA solutions to ensure their adherence to PBL principles and thus wider adoption of the created tools. What is important, is for the future PBL tools to be flexible and easily adapted to the needs of specific users and settings. There is no one model of PBL that is implemented in single format at all institutions, which makes it challenging to apply one set of generalizable practices and concepts to analyse and assess learning within PBL (Savin-Baden, 2004).

CONCLUSION

Even though the existing LA tools supporting PBL or PBL-related themes still have significant limitations, the ideas that they represent are valuable. In the era of a growing popularity of online learning and MOOCs, it is necessary to develop and provide tools that will make it possible to implement PBL process in different settings, also those that cannot afford the number of facilitators sufficient for effective support of all the enrolled students. Automation of feedback and assessment provide an opportunity for employing PBL at a larger scale, not only in small classrooms, while preserving its main principles. LA tools do have the potential to support students in developing collaboration, reflection, and self-directed learning skills, and to give the teachers information that can help them provide successful facilitation. Moreover, as the field is still struggling with making the

connection to the learning sciences, PBL practitioners can offer their experience, expertise, and critical perspective, to ensure that LA are indeed about learning, and not about showing performance. From the economic and institutional perspective, if constructivist approaches to learning are to maintain their position in education and continue to be adopted, they could potentially need to address the administrative limitations that are currently holding them back. LA, or specifically MMLA features are a way to possibly analyse and quantify non-traditional (or non-behaviourist) approaches to learning in order to give them an advantage in the educational systems driven by the political and economic need to demonstrate performance (Blikstein & Worsley, 2016). It may therefore be a smart move for PBL practitioners to engage with the field of LA, not only to benefit from the information it provides, but also to gain a voice in the change processes associated with the institutional and political adoption of digital technologies and LA. As we briefly discussed in the section *The reasons for the continuous growth of the field*, there are different perspectives driving the interests within LA: a research-led perspective focusing on learning, but equally a political-institutional perspective driven by an interest in increasing retention and minimising drop-out rates. While the latter is commendable, we need, as PBL practitioners, to ensure that adoptions of LA within PBL-institutions empower students and support collaboration, self-directed learning, and reflection.

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References

Ali, Z. F., Al-Dous, K., & Samaka, M. (2015). Problem-based learning environments in Moodle: Implementation approches. *2015 IEEE Global Engineering Education Conference (EDUCON)*, 868–873. https://doi.org/10.1109/EDUCON.2015.7096075

Almutairi, F. M., Sidiropoulos, N. D., & Karypis, G. (2017). Context-Aware Recommendation-Based Learning Analytics Using Tensor and Coupled Matrix Factorization. *IEEE Journal of Selected Topics in Signal Processing*, *11*(5), 729–741. https://doi.org/10.1109/JSTSP.2017.2705581

Bakharia, A., & Dawson, S. (2011). SNAPP: A Bird'S-eye View of Temporal Participant Interaction. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*, 168–173. https://doi.org/10.1145/2090116.2090144

Berland, M., Davis, D., & Smith, C. P. (2015). AMOEBA: Designing for collaboration in computer science classrooms through live learning analytics. *International Journal of Computer-Supported Collaborative Learning*, *10*(4), 425–447. https://doi.org/10.1007/s11412-015-9217-z

Blikstein, P. (2013). Multimodal Learning Analytics. *Proceedings of the Third International Conference on Learning Analytics and Knowledge*, 102–106. https://doi.org/10.1145/2460296.2460316

Blikstein, P., & Worsley, M. (2016). Multimodal Learning Analytics and Education Data Mining: Using Computational Technologies to Measure Complex Learning Tasks. *Journal of Learning Analytics*, *3*(2), 220–238. https://doi.org/10.18608/jla.2016.32.11

Bodily, R., & Verbert, K. (2017). Trends and Issues in Student-facing Learning Analytics Reporting Systems Research. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 309–318. https://doi.org/10.1145/3027385.3027403

Bolton, G. (2005). *Reflective Practice: Writing and Professional Development. Second Edition*. Paul Chapman Publishing, a SAGE Publications Company, Customer Care, 2455 Teller Road, Thousand Oaks, CA 91320.

Camacho, H., Skov, M., Jonasen, T. S., & Ryberg, T. (2018). Pathway to support the adoption of PBL in open data education. *Design and Technology Education: An International Journal*, *23*(2), 175–193.

Caviglia, F., Dalsgaard, C., Davidsen, J., & Ryberg, T. (2018). Studerendes digitale læringsmiljøer: læringsplatform eller medieøkologi? *Tidsskriftet Læring Og Medier (LOM)*, *10*(18). https://doi.org/10.7146/lom.v10i18.96928

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A Reference Model for Learning Analytics. *Int. J. Technol. Enhanc. Learn.*, *4*(5/6), 318–331. https://doi.org/10.1504/IJTEL.2012.051815

Dawson, S., Macfadyen, L., Risko, E., & Foulsham, T. (2012). *Using technology to encourage self-directed learning: The Collaborative Lecture Annotation System (CLAS)*. Presented at the ASCILITE 2012 - Annual conference of the Australian Society for Computers in Tertiary Education.

de Laat, M., Lally, V., Lipponen, L., & Simons, R.-J. (2007). Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for Social Network Analysis. *International Journal of Computer-Supported Collaborative Learning*, *2*(1), 87–103. https://doi.org/10.1007/s11412-007-9006-4

Dede, C. (2010). Comparing frameworks for 21st century skills. In J. Bellance & R. Brandt (Eds.), *21st Century Skills: Rethinking How Students Learn. Bloomington* (pp. 51–76). Bloomington: Solution Tree Press.

Dietrichson, A. (2013). Beyond Clickometry: Analytics for Constructivist Pedagogies. *International Journal on E-Learning*, *12*(4), 333–351.

Dohn, N. B., Sime, J.-A., Cranmer, S., Ryberg, T., & de Laat, M. (2018). Reflections and Challenges in Networked Learning. In N. Bonderup Dohn, S. Cranmer, J.-A. Sime, M. de Laat, & T. Ryberg (Eds.), *Networked Learning: Reflections and Challenges* (pp. 187–212). https://doi.org/10.1007/978-3-319-74857-3_11

Duval, E. (2011). Attention Please!: Learning Analytics for Visualization and Recommendation. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*, 9–17. https://doi.org/10.1145/2090116.2090118

Ellis, R. A., Han, F., & Pardo, A. (2017). Improving Learning Analytics – Combining Observational and Self-Report Data on Student Learning. *Journal of Educational Technology & Society*, *20*(3), 158–169.

Fawns, T. (2018). Postdigital Education in Design and Practice. *Postdigital Science and Education*. https://doi.org/10.1007/s42438-018-0021-8

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5–6), 304–317. https://doi.org/10.1504/IJTEL.2012.051816

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., … Vuorikari, R. (2016). *Research Evidence on the Use of Learning Analytics* (No. EUR 28294 EN). Retrieved from Joint Research Centre Science for Policy Report website: http://publications.jrc.ec.europa.eu/repository/bitstream/JRC104031/lfna28294enn.pdf

Ferguson, R., & Clow, D. (2017). Where is the Evidence?: A Call to Action for Learning Analytics. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 56–65. https://doi.org/10.1145/3027385.3027396

Fischer, F. (2015). *CSCL and Learning Analytics: Opportunities to Support Social Interaction, Self-Regulation and Socially Shared Regulation*.

Gandomkar, R., & Sandars, J. (2018). Clearing the confusion about self-directed learning and self-regulated learning. *Medical Teacher*, *40*(8), 862–863. https://doi.org/10.1080/0142159X.2018.1425382

García, F. B., & Benlloch-Dualde, J. V. (2016). Learning analytics sources: Beyond learning platforms. *2016 International Symposium on Computers in Education (SIIE)*, 1–6. https://doi.org/10.1109/SIIE.2016.7751834

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

General Call | Learning Analytics & Knowledge 2017. (n.d.). Retrieved 1 December 2016, from http://educ-lak17.educ.sfu.ca/index.php/general-call/

Gibson, A., Aitken, A., Sándor, Á., Buckingham Shum, S., Tsingos-Lucas, C., & Knight, S. (2017). Reflective Writing Analytics for Actionable Feedback. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 153–162. https://doi.org/10.1145/3027385.3027436

Graaff, E. D., & Kolmos, A. (2003). Characteristics of problem-based learning. *International Journal of Engineering Education*, 657–662.

Griffin, P., & Care, E. (2015). The ATC21S Method. In P. Griffin & E. Care (Eds.), *Assessment and Teaching of 21st Century Skills: Methods and Approach*. Retrieved from https://www.springer.com/gp/book/9789401793940

Herder, T., Swiecki, Z., Fougt, S. S., Tamborg, A. L., Allsopp, B. B., Shaffer, D. W., & Misfeldt, M. (2018). Supporting Teachers' Intervention in Students' Virtual Collaboration Using a Network Based Model. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*, 21–25. https://doi.org/10.1145/3170358.3170394

Hiemstra, R. (1999). Self-Directed Learning. In W. J. Rothwell & K. J. Sensenig (Eds.), *The Sourcebook for Self-directed Learning* (pp. 9–19). Human Resource Development.

Hogaboam, P. T., Chen, Y., Hmelo-Silver, C. E., Lajoie, S. P., Bodnar, S., Kazemitabar, M., … Chan, L. K. (2016). Data Dashboards to Support Facilitating Online Problem-Based Learning. *Quarterly Review of Distance Education; Charlotte*, *17*(3), 75-91,95-97.

Holtz, P., Sabol, V., Maturana, R. A., Troullinou, P., d'Aquin, M., Kowald, D., … Gadiraju, U. (2017, September 12). *AFEL: Towards measuring online activities contributions to self-directed learning*. Retrieved from https://aran.library.nuigalway.ie/handle/10379/7466

Joksimović, S., Manataki, A., Gašević, D., Dawson, S., Kovanović, V., & de Kereki, I. F. (2016). *Translating network position into performance: importance of centrality in different network configurations*. 314–323. https://doi.org/10.1145/2883851.2883928

Khalil, M., & Ebner, M. (2015, June 22). *Learning Analytics: Principles and Constraints*. https://doi.org/10.13140/RG.2.1.1733.2083

Kilińska, D., Kobbelgaard, F., & Ryberg, T. (2018, September). *Learning analytics features for improving collaborative writing practices: Insights into the students' perspective.* Presented at the International Council of Educational Media Conference, Tallinn, Estonia.

Koh, E., Shibani, A., Tan, J. P.-L., & Hong, H. (2016). A Pedagogical Framework for Learning Analytics in Collaborative Inquiry Tasks: An Example from a Teamwork Competency Awareness Program. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, 74–83. https://doi.org/10.1145/2883851.2883914

Kolmos, A., Fink, F. K., & Krogh, L. (2004). *The Aalborg PBL Model - Progress Diversity and Challenges*. Aalborg: Aalborg University Press.

Kovanović, V., Joksimović, S., Mirriahi, N., Blaine, E., Gašević, D., Siemens, G., & Dawson,
S. (2018). Understand Students' Self-reflections Through Learning Analytics.
Proceedings of the 8th International Conference on Learning Analytics and Knowledge,
389–398. https://doi.org/10.1145/3170358.3170374

Lonn, S., Krumm, A. E., Waddington, R. J., & Teasley, S. D. (2012). Bridging the Gap from
Knowledge to Action: Putting Analytics in the Hands of Academic Advisors.
*Proceedings of the 2Nd International Conference on Learning Analytics and
Knowledge*, 184–187. https://doi.org/10.1145/2330601.2330647

Luhrs, C., & McAnally-Salas, L. (2016). Collaboration Levels in Asynchronous Discussion
Forums: A Social Network Analysis Approach. *Journal of Interactive Online Learning*,
14(1), 29–44.

Mangaroska, K., & Giannakos, M. N. (2018). Learning analytics for learning design: A
systematic literature review of analytics-driven design to enhance learning. *IEEE
Transactions on Learning Technologies*, 1–1.
https://doi.org/10.1109/TLT.2018.2868673

Mehaffy, G. L. (2012). Challenge and Change. *EDUCAUSE Review*, *47*(5), 25.

Nicholl, T. A., & Lou, K. (2012). A Model for Small-Group Problem-Based Learning in a
Large Class Facilitated by One Instructor. *American Journal of Pharmaceutical
Education*, *76*(6). https://doi.org/10.5688/ajpe766117

Ochoa, X., & Worsley, M. (2016). Editorial: Augmenting Learning Analytics with Multimodal
Sensory Data. *Journal of Learning Analytics*, *3*(2), 213–219.
https://doi.org/10.18608/jla.2016.32.10

Rabbany k., R., Takaffoli, M., & Zaïane, O. R. (2012). Social network analysis and mining to
support the assessment of on-line student participation. *ACM SIGKDD Explorations
Newsletter*, *13*(2), 20. https://doi.org/10.1145/2207243.2207247

Risko, E. F., Foulsham, T., Dawson, S., & Kingstone, A. (2013). The Collaborative Lecture
Annotation System (CLAS): A New TOOL for Distributed Learning. *IEEE
Transactions on Learning Technologies*, *6*(1), 4–13.
https://doi.org/10.1109/TLT.2012.15

Romero, C., López, M.-I., Luna, J.-M., & Ventura, S. (2013). Predicting students' final
performance from participation in on-line discussion forums. *Computers & Education*,
68, 458–472. https://doi.org/10.1016/j.compedu.2013.06.009

Rubel, A., & Jones, K. M. L. (2016). Student privacy in learning analytics: An information
ethics perspective. *The Information Society*, *32*(2), 143–159.
https://doi.org/10.1080/01972243.2016.1130502

Ryberg, T., Koottatep, S., Pengchai, P., & Dirckinck-Holmfeld, L. (2006). Conditions for
productive learning in networked learning environments: a case study from the

VO@NET project. *Studies in Continuing Education*, *28*(2), 151–170. https://doi.org/10.1080/01580370600751138

Saqr, M., Fors, U., & Nouri, J. (2018). Using social network analysis to understand online Problem-Based Learning and predict performance. *PLOS ONE*, *13*(9), e0203590. https://doi.org/10.1371/journal.pone.0203590

Savery, J. R. (2006). Overview of Problem-based Learning: Definitions and Distinctions. *Interdisciplinary Journal of Problem-Based Learning*, *1*(1). https://doi.org/10.7771/1541-5015.1002

Savin-Baden, M. (2004). Understanding the impact of assessment on students in problem-based learning. *Innovations in Education and Teaching International*, *41*(2), 221–233. https://doi.org/10.1080/1470329042000208729

Savin-Baden, M. (2007). Challenging PBL models and Perspectives. In E. D. Graaff & A. Kolmos (Eds.), *Management of Change - Implementation of Problem-Based and Project-Based Learning in Engineering* (pp. 9–30). Rotterdam: SensePublishers.

Sclater, N., Webb, M., & Danson, M. (2017). The future of data-driven decision-making. Retrieved from https://www.jisc.ac.uk/reports/the-future-of-data-driven-decision-making

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2018). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2018.05.004

Shum, S. B., & Crick, R. D. (2012). *Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics*. Presented at the 2nd International Conference on Learning Analytics & Knowledge, Vancouver, British Columbia, Canada. Retrieved from http://oro.open.ac.uk/32823/

Shum, S. B., & Crick, R. D. (2016). Learning Analytics for 21st Century Competencies. *Journal of Learning Analytics*, *3*(2), 6–21. https://doi.org/10.18608/jla.2016.32.2

Siemens, G. (2010, July 22). 1st International Conference on Learning Analytics and Knowledge 2011 | Connecting the technical, pedagogical, and social dimensions of learning analytics. Retrieved 5 November 2018, from 1st International Conference on Learning Analytics and Knowledge 201 website: https://tekri.athabascau.ca/analytics/

Silva, E. (2009). Measuring Skills for 21st-Century Learning. *Phi Delta Kappan*, *90*(9), 630–634. https://doi.org/10.1177/003172170909000905

Simon, J. (2017). A Priori Knowledge in Learning Analytics. In A. Peña-Ayala (Ed.), *Learning Analytics: Fundaments, Applications, and Trends* (pp. 199–227). https://doi.org/10.1007/978-3-319-52977-6_7

Slade, S., & Prinsloo, P. (2013). Learning Analytics Ethical Issues and Dilemmas. *American Behavioral Scientist*, *57*(10), 1510–1529. https://doi.org/10.1177/0002764213479366

Sørensen, M. T. (2018). The Students' Choice of Technology A pragmatic and outcome-focused Approach. In D. Kergel, B. Heidkamp, P. K. Telléus, T. Rachwal, & S. Nowakowski (Eds.), *The Digital Turn in Higher Education* (pp. 161–174). https://doi.org/10.1007/978-3-658-19925-8_12

Spikol, D., Ruffaldi, E., & Cukurova, M. (2017). *Using Multimodal Learning Analytics to Identify Aspects of Collaboration in Project-Based Learning*. Retrieved from https://repository.isls.org/handle/1/240

Suraj, P., & Roshni, V. S. K. (2015). Social network analysis in student online discussion forums. *2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, 134–138. https://doi.org/10.1109/RAICS.2015.7488402

Swenson, J. (2014). *Establishing an ethical literacy for learning analytics*. 246–250. https://doi.org/10.1145/2567574.2567613

Tabuenca, B., Kalz, M., Drachsler, H., & Specht, M. (2015). Time will tell: The role of mobile learning analytics in self-regulated learning. *Computers & Education*, *89*, 53–74. https://doi.org/10.1016/j.compedu.2015.08.004

Taylor, J. C. (2001). *Automating e-Learning: The Higher Education Revolution*.

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157–167. https://doi.org/10.1016/j.chb.2014.05.038

Thorpe, K. (2004). Reflective learning journals: From concept to practice. *Reflective Practice*, *5*(3), 327–343. https://doi.org/10.1080/1462394042000270655

Towndrow, P. A., Ling, T. A., & Venthan, A. M. (2008). Promoting Inquiry Through Science Reflective Journal Writing. *Eurasia Journal of Mathematics, Science and Technology Education*, *4*(3), 279–283. https://doi.org/10.12973/ejmste/75350

Triantafyllou, E., Xylakis, E., Nilsson, N., & Timcenko, O. (2018). Employing learning analytics for monitoring student learning pathways during Problem-Based Learning group work: a novel approach. *Proceedings of the 7th International Research Symposium on PBL*. Presented at the IRSPBL 2018: Innovation, PBL and Competences, Beijing, China.

Triantafyllou, E., Xylakis, E., Zotou, M., Tambouris, E., & Tarabanis, K. (2018). Applying Learning Analytics in Problem-Based Learning Engineering Semester Projects. *Proceedings of the SEFI 2018*. Presented at the SEFI annual Conference 2018: Creativity, Innovation and Entrepreneurship for Engineering Education Excellence, Copenhagen, Denmark.

Ullmann, T., Fridolin, W., & Scott, P. (2012). Comparing Automatically Detected Reflective Texts with Human Judgements. *2nd Workshop on Awareness and Reflection in Technology-Enhanced Learning*, 101–1016. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.371.1382&rep=rep1&type=pdf

van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2014). Supporting teachers in guiding collaborating students: Effects of learning analytics in CSCL. *Computers & Education*, *79*, 28–39. https://doi.org/10.1016/j.compedu.2014.07.007

West, D., Huijser, H., & Heath, D. (2016). Putting an ethical lens on learning analytics. *Educational Technology Research and Development*, *64*(5), 903–922. https://doi.org/10.1007/s11423-016-9464-3

Williamson, B. (2016). Digital education governance: data visualization, predictive analytics, and 'real-time' policy instruments. *Journal of Education Policy*, *31*(2), 123–141. https://doi.org/10.1080/02680939.2015.1035758

Williamson, B. (2017). *Big data in education: the digital future of learning, policy and practice* (1st ed.). Thousand Oaks, CA: SAGE Publications.

Wilson, A., Watson, C., Thompson, T. L., Drew, V., & Doyle, S. (2017). Learning analytics: challenges and limitations. *Teaching in Higher Education*, *22*(8), 991–1007. https://doi.org/10.1080/13562517.2017.1332026

Wise, A. F. (2014). Designing Pedagogical Interventions to Support Student Use of Learning Analytics. *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge*, 203–211. https://doi.org/10.1145/2567574.2567588