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Integrating Learning Analytics Into Engineering Education: Design Strategies For Teachers

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Background, Rationale and Motivation

While reflecting on the role of engineering education for a sustainable world, one must consider one of the most important gamechangers in education of this century: the use of big data, and within it, Learning Analytics (LA).

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” (Gasevic *et al.,* 2019; Long *et al.*, 2011). LA generally comprises three major themes: indicators and predictors, visualizations, and interventions (Gasevic *et al*. 2019; Brown, 2012) which are interconnected. For instance, specific Learning Analytics indicators can be developed and subsequently used to visualize critical areas of the learning experience to provide the basis for the design of class interventions. Some examples may include: basic summary indicators such as total learning time online and total number of learning sessions (Conijn et al., 2017), study irregularity indicators such as irregularity of learning time and entropy (Jovanovic et al., 2019), and indicators of resource accessing such as number of file downloads and number of forum posts (Park et al., 2016). Indicators have been found to be predictive of students’ learning outcomes (Conijn *et al*., 2017), beneficial forms of learning (Liz-Dominguez *et al.*, 2022) or student well-being (Sher *et al.*, 2022).

One important aspect of learning behavior often explored is student engagement, that has always been considered essential for successful learning, which modern LA methods have allowed us to get a deeper understanding of this process (Saqr & Lopez-Pernas, 2021). Student engagement is a fluid and dynamic process, and can change over the duration of the course, year, or even the whole study program (Saqr & Lopez-Pernas, 2021). Such trajectories are difficult and costly to measure with more traditional methods (such as surveys or interviews) (Panadero, 2016).

Educational professionals can utilize these insights to identify students’ needs and design educational interventions that can help students improve (Charleer *et al.*, 2016). Big data from individual students can be used to create personalized learning approaches and targeted interventions that account for particular needs and goals (Zhang et al., 2020). Interventions would need to be done early enough during a course so that students can adjust their learning behavior over time. Also, teachers would need to design their course and interventions so that students' online learning behavior generates data required by the indicators.

Workshop activities

We will initially present the background of LA and set the scene on type

of indicators and tools for data visualisation. We will use the workshop design of Hrastinski (2021) so that participants consider their own courses and work in small groups. The groups will be based on type of indicator (to support student learning outcomes/student wellbeing/personalized learning and student engagement).
In this way each participant can get useful information for its own course from this workshop. The following points will be considered within the groups:

1. Background – Share your own module, e.g. name, purpose, level, scope/credits, approximate number of participants
2. Design -Describe and motivate the indicators incorporated in the course design
3. Evaluate - How should the indicators be visualized and interpretated to make informed decisions?
4. What potential ethical challenges may arise, and how can they be effectively addressed?
5. Share - How can lessons learned be shared with colleagues?

We will use posters in each 'round table' to record the outputs of the idea generation. Finally, we will bring all the ideas together in a plenary discussion where all participants can share lessons and challenges they might face.

Presentation	20 min
Group work	15 min
Plenary discussion	15 min
Concluding remarks	5 min

Workshop objectives

This workshop provides an opportunity for engineering educators to learn about LA, how it can be incorporated in their course design and what LA literacy do teachers and students need to take advantage of this approach. This will in turn improve student learning outcomes, address student behaviour with respect to performance and improve personalized learning (Akhila et al, 2020).

One aspect that we will cover throughout is the ethical usage of big data in education. Using technology that can store and identify the trace data of individual students leads to the possibility of tracking learners (Pardo & Siemens, 2014) and hence give rise to ethical and privacy issues that require understanding and active effort from educators, researchers, and policy makers to solve. We will present some of the frameworks and models that have been created for this (Kitto & Knight, 2019).
At the end of the workshop participants would be able to a) list different indicators (e.g. to support student's achievement of learning outcomes and or student well-being), b) grasp the basis of course design to generate useful data for different types of indicators in an ethical, transparent and responsible manner and c) identify tools

that can support the interpretation of data that supports their decisions on course design in engineering education.

Workshop outcomes

The workshop discussed broadly the opportunities provided by LA and was visited by an enthusiastic range of researchers and practitioners looking to improve students learning in engineering education through the use of educational data. The presentation clarified the use of data by teachers to improve their course, by students to improve performance and by the institution to improve student retainment and wellbeing and overall management information.

After setting the scene in the presentation the group naturally split into three differently focused groups. There was a group grasping the set up of LA to improve student engagement, sharing experiences and discussing further on the possibilities presented. There was special interest in the direct feedback loop towards students and on ‘how to communicate’ the outcomes of the data analyses to improve student engagement. Another group focused on monitoring student wellbeing, discussing the friction between LA on course level and balancing the student workload on curriculum level. Furthermore, the ethical considerations regarding opting out vs informed consent on the use of student data rose the question: ‘what is really helping the student?’. Here, also the importance of combining offline and online student data was stressed. The third group discussed in more detail the use of LA to measure student self regulated learning and the use of resources. The group discussed the way in which the feasibility of unobtrusive measurement of students’ learning characteristics can be tested, and the results of a working paper in which this approach was shown to work well for three of four dimensions of self-regulated learning. The discussion highlighted the need to think carefully about how to design a course in such a way that it delivers useful input for a learning analytics approach.

Conclusions

Using LA starts at most institutions with smaller scale pilots in individual courses. The set up of LA requires a lot of investment by different stakeholders at the institution because on the one hand little is known yet and on the other hand the local legislation and privacy requirements prohibit a ‘one size fits all’ solution. Unfortunately, small scale pilots do not provide the needed overall picture that is required to compose a meaningful and personalized analysis and advice for students. For student engagement, student wellbeing, student performance and the improvement of courses a lot of different dots have to be connected, in the ideal world this would be online as well as offline indicators.

However the small scale pilots deliver a meaningful and essential contribution to the development of LA at scale. The use of LA for self regulated learning is an example. LA pilot projects are pieces of the puzzle to realize the above ideal world and contribute to the large scale adoption of Learning Analytics that is an unevitable development in the current developments of big data. Despite differences in regulation and privacy, the experiences of different institutions can together optimize the development of learning analytics at scale.

Significance for engineering education

This workshop provided an opportunity for engineering educators to learn about LA and how to incorporate it in engineering education and course design.

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Slides: https://rb.gy/s8pcx

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