Behind the Scenes: Designing a Learning Analytics Platform for Higher Education

Irene-Angelica Chounta, Margus Pedaste, Katrin Saks
University of Tartu
{chounta, margus.pedaste, katrin.saks}@ut.ee

ABSTRACT: In this paper we share our experience from designing a Learning Analytics platform to support the needs of stakeholders from a higher-education academic institution in Estonia. We present the design framework and the architecture of our platform and we discuss how we aim to address challenges imposed by context. For the design of the platform, we carried out interviews with students, teachers and stakeholders from the institution's administration in order to gain insight with respect to the needs of users. Here, we report our findings from these studies, but we specifically focus on the teachers' perspective. Finally, we conclude to a discussion about lessons learned from our interviews with teachers and the proposed design framework of the LA platform in its first steps.

Keywords: learning analytics, design framework, teachers, requirements

1 INTRODUCTION

The use of computational methods to analyze the learning process and to improve the learning outcomes is commonly described by the term "*Learning Analytics*" (Siemens, 2013). Learning Analytics (LA) in Higher Education mainly aim to support students and instructors in monitoring, mirroring and guiding (Jermann, Soller, & Muehlenbrock, 2001) by providing adaptive and personalized feedback. Usually, feedback is offered through student or teacher dashboards using visualizations and graph representations (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). Such dashboards present informative statistics and visualizations of "meaningful" student activity. That is, student actions that may indicate either learning or some kind of disruption of the learning process (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). It is argued that the use of metrics of student activity may provide false assessments of learning, mainly because such metrics come from data-driven approaches and are not theoretically grounded using pedagogical reasoning (Duval, 2011; Gašević, Dawson, & Siemens, 2015). In addition, activity metrics, charts and statistics can be interpreted in more than one ways leading to misunderstandings and misinterpretations (Spada, Meier, Rummel, & Hauser, 2005).

Our main objective is to design and implement learning analytics and feedback mechanisms to support the practice of stakeholders from the academic community of the University of Tartu. The University of Tartu is a leading centre of research and training in Estonia and it consists of 4 faculties: Faculty of Arts and Humanities, Faculty of Social Sciences, Faculty of Medicine and Faculty Science and Technology. It offers a wide range of bachelor, master and phD study programs for about 13000 students[1]. Stakeholders in this context are the students and the teachers (or instructors) of the university. The learning analytics we aim to design, are based on computational models that aim to assess the student's academic performance, to identify risks and to prevent possible failures (such as drop-outs) and to provide personalized and adaptive feedback to students. By computational models, we mean predictive approaches to assess a dependent variable (for example, academic performance) with respect to independent variables (for example, points earned in the current course from assignments, students' contribution in group projects or group discussions, resources access patters, etc.). As data inputs, we use three data sources: a) demographics and data about the student's history, as recorded by the Study Information System (SIS) of the university; b) data from courses that the student has participated, as recorded by the university's Learning Management System (LMS); c) data from direct student input, such as questionnaires and learning artefacts (for example, homework). The goal is to use the assessments of the computational analytics to provide appropriate interventions (for example, feedback and recommendations) for students in order to improve learning outcomes and for teachers in order to support their practice.

We strive to follow an evidence-based (Ogata, Majumdar, Akçapınar, Hasnine, & Flanagan, 2018) design approach and design a computational approach that can be backed up by rigorous pedagogy. Most importantly, we want to provide tools to teachers and students that "make sense". That is, tools that can support their needs and that can be easily and effortlessly integrated in their every-day practice. Educational technologies and, in particular, learning analytics are topics that attract research interest. However, successful integration of new technologies and computational tools into the classrooms has been so far slow and hard to achieve (Ferguson et al., 2016). Teachers, in particular, feel disconnected from research outcomes and don't see how new technologies support their needs[2]. In this paper, we present our experiences from designing a new learning analytics platform with the goal to bridge the gap between research and practice. In particular, during the design phase of the platform, we followed a socio-technical approach. We asked stakeholders (teachers, students, administration and policy makers) to contribute to the design by participating in interviews and focus groups. Here, we focus on the teachers' perspective, as it was captured in a focus group and we discuss how their input contributed to the design framework of the learning analytics platform.

2 METHOD OF STUDY

To support the design of the learning analytics platform, we conducted interviews and focus groups with stakeholders in two rounds (**Figure 1**). In the first round, the aim was to discuss with stakeholders potential LA mechanisms (in total, we asked the stakeholders to review 21 LA mechanisms) – both for students and teachers – to support different objectives of the contemporary learning approach (Pedaste & Leijen, 2018) and how we can adapt these mechanisms to facilitate our university's needs. For the first round, we carried out two focus group interviews. The first interview was conducted with teachers, program directors, LMS administrators and a specialist in educational technology (N=10), all having long-term experience with LMSs. The participants of the second interview were undergraduate students (N=6) who all had one or two years of experience with LMSs.

[1] https://www.ut.ee/en/university/general
[2] https://www.edsurge.com/news/2018-09-26-what-can-machine-learning-really-predict-in-education

In the second round, we focused on teachers' practices and needs. Therefore, we carried out a series of activities over an academic semester where we asked from four teachers – who were sharing a blended-learning course – to use a set of educational technologies to organize this course. At the end of the semester, we carried out a focus group discussion with 3 out of the 4 teachers who worked with us during the semester (from now on we refer to them as I1, I2 and I3). During the discussion we went over the teachers' work practices, we discussed about their needs and how technology addressed these needs, as well as their expectations from learning analytics. The discussion was facilitated by an experienced research in Human-Computer Interaction topics, Educational Technologies and Learning Analytics. The discussion lasted for about an hour and it was recorded - after having acquired the instructors' consent. After the end of the discussion, the recordings have been transcribed and analyzed.

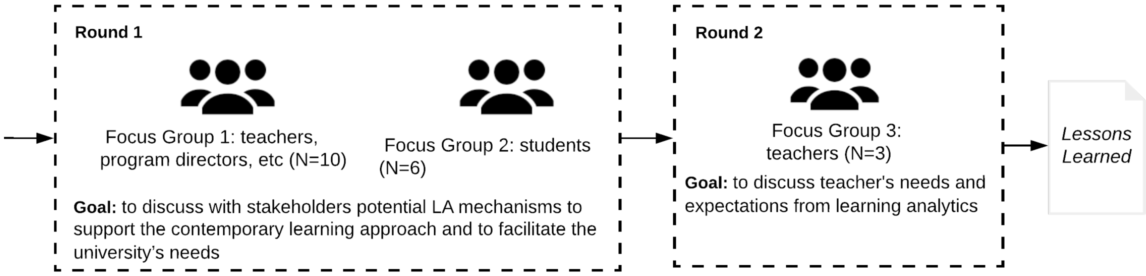

Figure 1. The interviews and focus groups process described in this work

3 LESSONS LEARNED

Here, we present the outcomes from the two discussion-with-stakeholders rounds in the form of "lessons learned". In this sense, we use stakeholders' input as practical guidelines that can support us in the design and implementation of our LA framework. From the first round, the analysis of the focus groups discussions showed that self-regulation and subject knowledge acquisition makes sense for stakeholders to be supported in combination by LA. Stakeholders also stated that more attention should be paid to supporting collaboration and subjective well-being. At the same time, it was mentioned that the value of LA requires more in-depth analysis. Our focus group interviews showed students to be slightly more positive towards using different applications of LA, whereas only a few scenarios were considered useful by most of the teachers and high variation was found in teachers' questionnaires replies (Saks, Pedaste, & Rannastu, 2018). In order to further explore the high variation in teachers' perspective regarding LA, we conducted the second round of focus group discussions (described in section 2) only with teachers. This discussion was structured in three parts that explored teachers' user experience with educational technologies, their perception about usability of such technologies and future directions that could be supported by LA.

The analysis of the discussion showed that teachers are in favor of LA tools that support tracking the progress of students with respect to competencies or skills and they envisioned a technology that would allow them to track progress regarding different activities in one bigger picture (**I3**: "*We wanted our students to upload their tasks, their pictures and we wanted to see how they change these… we wanted to see their progress*"). They pointed out that the nature of the course did not allow them to act on a predefined plan, but they had to adapt their teaching strategies to the students' needs (**I3**: "*it was the professional development course and you lay on students' needs*"). This made the need for LA tools to support their practice more prominent. Due to the blended-learning nature of the course, the teachers used in combination various technologies (for example Google Apps, LMS and other educational software). This made it difficult for them to track the students' progress and interactions with learning objects and therefore the teachers pointed out that there was a need for a tool that would provide them with an overview of students' activity (**I3**: "*we would like to see how the students make these changes… we wanted to see the progress but couldn't find the right tool for that*"). With respect to the way we present information about students' activity, the teachers first of all mentioned issues of privacy. In particular, the teachers informed us that students are usually uncomfortable when sharing information or materials with their peers (**I2**: "*in my group the problem was that this was visible to everybody and the students said I don't want to put anything there*"). At the same time, teachers have concerns about the visibility level of their own materials and information. When they don't have a clear idea about the visibility status of their activities, it makes them feel uncertain and leads then to take additional action (for example, to send emails) in order to confirm that the students can see certain information.

For the last part of the focus group, we asked the teachers to discuss what kind of expectations they have from technology. Teachers stated that they strongly feel the need for tools that will support them to manage their time efficiently and at the same time allow them to have a clear picture of how (and how often) the students engage with learning material and activities. This helps them to assess the students' progress and to plan their teaching strategies (**I2**: "*for me it's important to know that the student has not disappeared, but he visits from now and then. Another thing I follow is that they regularly practice their exercises. If they don't, I usually send out emails and remind them*"). They pointed out the need for tools that present basic traffic information. We followed up and asked them what kind of input they would like to receive from the system (visualizations, alarms, text messages). The instructors responded that graphs and percentages are difficult to read and require time to understand and interpret. One of the instructors referred to a past brainstorm session they had and brought up an idea from this session: "*the idea was that when a student has not logged in for a number of days, then the program automatically sends the student a little friendly note e.g. "is everything ok?" "please come and visit us". At the same time the teacher will also receive a note that these students received that messages. If a student repeats this behavior, then the teacher gets a report based on the number of messages a student has received*" (**I2**). The same instructor stated that it is important for them not to have to follow each and every student on a regular basis but only to receive information on critical issues. The other instructors agreed that they are in favor of some kind of automated assessment that they could use to further investigate but they also pointed out that they would like to control the amount of information they receive (**I3**: "*I'm not sure I want too much information automatically. Maybe I prefer to do that manually*").

4 PRACTICAL IMPLICATIONS AND FUTURE WORK

We used the input from the focus groups in order to inform the design framework of the learning analytics platform at the University of Tartu (**Figure 2**). In particular, we focused on serving teachers' needs and therefore we put emphasis in their requirements. An outcome from our discussions with teachers was that even though teachers want to have a clear picture about students' activity, they often don't have time to review visualizations about students' progress or to go through statistics. On the contrary, they would prefer to receive automated or semi-automated messages or assessments that would use in order to further investigate specific cases. To that end, our design framework integrates LA tools that provide teachers with automatic assessments of student's performance or explicit alerts of potential problems. Such tools aim to assist teachers in adapting to student's needs easier, faster and to support them in deciding whether an intervention (and potentially what kind of intervention) is necessary (Chounta & Avouris, 2016; Holstein, McLaren, & Aleven, 2017).

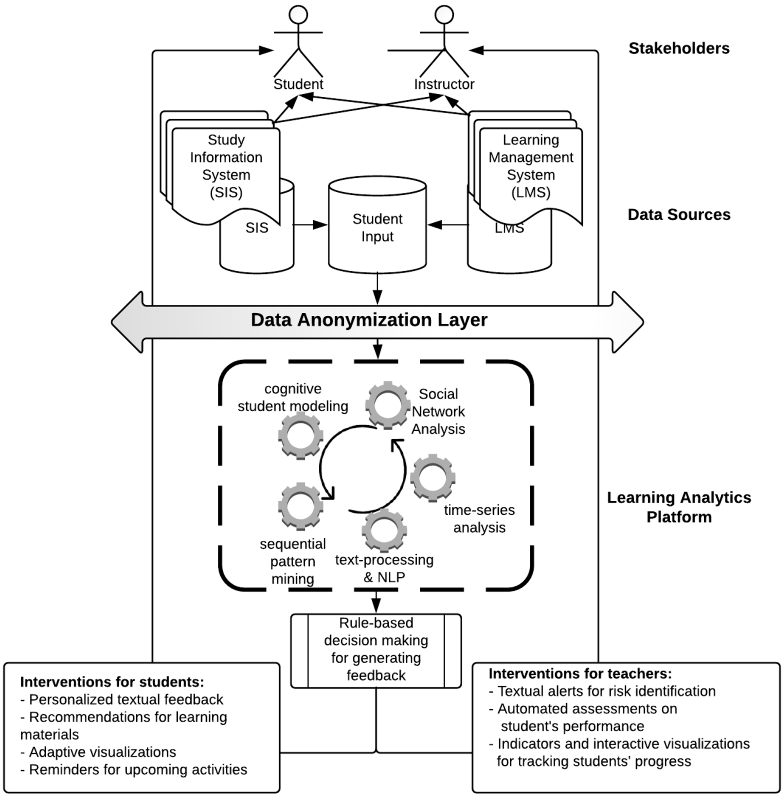

Figure 2. The proposed design framework of the Learning Analytics Platform at the University of Tartu after the interviews with stakeholders

Teachers also stated that it is important for them to track the progress of students with respect to specific skills and competencies. This is a well-established practice: Intelligent Tutoring Systems use the concept of Mastery Learning in order to provide learning materials or feedback to students who practice specific skills. To do that, they maintain individual student models (one model for each student) that provide an assessment of the student's knowledge state (Corbett, Koedinger, & Anderson, 1997). Similarly, we aim to apply cognitive modeling approaches to capture cognitive development (Chounta, Albacete, Jordan, Katz, & McLaren, 2017) and dynamic competence assessment of individual students using learning analytics to assess students' performance. Achieving this step will bring us closer to providing personalized and adaptive feedback to students as well as informative monitoring mechanisms to support teachers in planning and guiding.

ACKNOWLEDGEMENTS

This work was partly supported by the Estonian Research Council grant PSG286.

REFERENCES

Chounta, I.-A., Albacete, P., Jordan, P., Katz, S., & McLaren, B. M. (2017). The "Grey Area": A computational approach to model the Zone of Proximal Development. In *European Conference on Technology Enhanced Learning* (pp. 3–16). Springer.

Chounta, I.-A., & Avouris, N. (2016). Towards the real-time evaluation of collaborative activities: Integration of an automatic rater of collaboration quality in the classroom from the teacher's perspective. *Education and Information Technologies*, *21*(4), 815–835.

Corbett, A. T., Koedinger, K. R., & Anderson, J. R. (1997). Intelligent tutoring systems. In *Handbook of Human-Computer Interaction (Second Edition)* (pp. 849–874). Elsevier.

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

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and Implementation of a Learning Analytics Toolkit for Teachers. *Educational Technology & Society*, *15*(3), 58–76.

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., … Vuorikari, R. (2016). Research evidence on the use of learning analytics: Implications for education policy.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64–71.

Holstein, K., McLaren, B. M., & Aleven, V. (2017). Intelligent tutors as teachers' aides: exploring teacher needs for real-time analytics in blended classrooms. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 257–266). ACM.

Jermann, P., Soller, A., & Muehlenbrock, M. (2001). From mirroring to guiding: A review of the state of art technology for supporting collaborative learning. In & K. H. P. Dillenbourg A. Eurelings (Ed.), *Proceedings of the European Conference on Computer-Supported Collaborative Learning EuroCSCL-2001. Maastricht, The Netherlands* (pp. 324–331). Maastricht, Pays-Bas. Retrieved from http://telearn.archives-ouvertes.fr/hal-00197377

Ogata, H., Majumdar, R., Akçapınar, G., Hasnine, M., & Flanagan, B. (2018). Beyond Learning Analytics: Framework for Technology-Enhanced Evidence-Based Education and Learning. In *26th International Conference on Computers in Education*.

Pedaste, M., & Leijen, Ä. (2018). How Can Advanced Technologies Support the Contemporary Learning Approach? In *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)* (pp. 21–23). IEEE.

Saks, K., Pedaste, M., & Rannastu, M. (2018). University Teachers' and Students' Expectations on Learning Analytics. In *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)* (pp. 183–187). IEEE.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, *57*(10), 1380–1400.

Spada, H., Meier, A., Rummel, N., & Hauser, S. (2005). A New Method to Assess the Quality of Collaborative Process in CSCL. In *Proceedings of th 2005 Conference on Computer Support for Collaborative Learning: Learning 2005: The Next 10 Years!* (pp. 622–631). Taipei, Taiwan: International Society of the Learning Sciences. Retrieved from http://dl.acm.org/citation.cfm?id=1149293.1149375

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500–1509.