Analytics for Everyday Learning from two Perspectives: Knowledge Workers and Teachers

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Abstract. Learning analytics deals with tools and methods for analyzing and detecting patterns in order to support learners while learning in formal as well as informal learning settings. In this work, we present the results of two focus groups in which the effects of a learning resource recommender system and a dashboard based on analytics for everyday learning were discussed from two perspectives: (1) knowledge workers as self-regulated everyday learners (i.e., informal learning) and (2) teachers who serve as instructors for learners (i.e., formal learning). Our findings show that the advantages of analytics for everyday learning are three-fold: (1) it can enhance the motivation to learn, (2) it can make learning easier and broadens the scope of learning, and (3) it helps to organize and to systematize everyday learning.

Keywords: Learning analytics, recommender systems, focus group, informal learning, formal learning.

1 Introduction

"Learning analytics is 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." as stated by [16]. Thus, learning analytics deals beside others also with methods for analyzing and detecting patterns within digital data collected within educational settings or learning environments about the learner in order to support them. For applying learning analytics to everyday learners, the data collected encompasses implicit and explicit traces a learner has left on the Web, e.g., on Facebook or Twitter. These traces can also be mined for personalized recommendations [3], which is very helpful for learners to filter information such as the number of learning resources, learning activities etc. significantly increases. Such

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a recommender typically suggests further learning resources out of an overwhelming variety of choices adapted and personalized to the learner's interests and learning needs. While recommenders are well investigated in the area of technology-enhanced learning especially with respect to formal learning settings [15], less research has been addressed for recommenders based on analytics for everyday learning (i.e., informal learning).

In this work, we present the results of two focus groups that were conducted in two different settings focusing on a learning resource recommender based on analytics for everyday learning. The first focus group was conducted together with knowledge workers to discuss how a recommender can improve everyday learning while working and which indicators are relevant for measuring the improvements. The second focus group was conducted with teachers to discuss. After presenting the results of each focus group individually, we finally compare the results from both focus groups and discuss them from the two different perspectives, namely from the perspective of knowledge workers (i.e., self-regulated everyday learners) and teachers who serve as instructors for learners. As a result, the following three main claims are derived: analytics for everyday learning (1) can enhance the motivation to learn, (2) can make learning easier and broadens the scope of learning, and (3) helps to organize and to systematize everyday learning.

2 Related Work

Learning analytics deals with methods for analyzing and detecting patterns within data collected from educational settings or learning environments about the learner, and leverage those methods to support adaptation, personalization, reflection as well as recommendation.

Siemens [12] defines learning analytics as "*the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning*". The focus of learning analytics is on providing support for the learner in formal as well as informal learning settings, thus, also for everyday learning. Approaches like learning dashboards for example described in [3,9] present an overview of the learner's own learning activities and learning progress often in relation to colleagues at one glance. Such combined visualizations support self-monitoring of learners and awareness for teachers and empower the learners to reflect on their own activity and that of their peers. Explicit traces (e.g. the learner's entries in a chat or a discussion forum) and implicit traces (e.g. the learner entering a course or clicking on a document or button) stored in the corresponding learner profiles serve as basis for the aggregation and visualization of the gathered data. These explicit and implicit traces can be used to provide personalized access to learning material [1], which can be specifically prepared for such learning needs [14].
Learning analytics can provide guidance, especially in informal learning situations. This is relevant as most of the learning happens informally and as this type of learning

becomes more and more important [7]. Informal learning is either intentional or unintentional, non-institutional as well as not pre-structured, experiential and primarily under the control of the learner, and, furthermore, its outcomes are difficult to predict a priori [13]. In regard of informal learning, analytics is important to prompt reflection about the own behavior [4], which is very helpful for learners as the number of resources, learning activities etc. significantly increased, so that "*learners may find it hard to get an overview of the available learning activities and to identify the most suitable ones*" [2].

Additionally, analyzing the data streams can be used to provide suitable recommendations to the learners in informal learning situations [10]. The major goal of recommenders is to assist users to find items of their interest or related to their learning goal [8] by suggesting potential useful items to a learner. As a result, recommender systems are widely common in the area of technology-enhanced learning, as "*it is difficult to express specific learning requirements through keywords*" [15]. Therefore, learning environments often provide recommendations to learning resources but do not ensure if a learner or teacher really use the suggested resources [15]. However, from the content perspective, tools for selecting and preparing learning material are needed [11]

The major goal of all these approaches is to use learning analytics as underlying approach to support learners while learning, irrespective of whether it is formal or informal learning. Our focus thereby is to provide support by reducing the abundance of information and by providing learning recommendations tailored to the learner's needs and preferences. Therefore, in this work, we want to address, which improvements for learning can be achieved with recommendations and which indicators might be useful to measure the usefulness of the recommendation. We will discuss this in the remainder of this paper.

3 Procedure

We conducted two different focus groups following nearly the same procedure to answer more or less the same research questions but from two different perspectives. Additionally, the first focus group the focus was put solely on the resource recommender system, while in the second focus group also a dashboard for teachers was discussed. Therefore, two separately conducted focus groups were necessary because of two reasons. First, parts of the results gained from the focus group conducted first were taken as initial starting point for the second focus group. Second, we want to shed light on our research questions from two different perspectives: from the perspective of knowledge workers as everyday learners and from the perspective of active teachers who serve as instructors for learners.

3.1 Research Context

Our research took place in a project focusing on analytics for everyday learners. One of the tools developed in this project is a mobile application that includes a learning

resource recommender for everyday learning. In general, the app allows learners to monitor their own learning progress in the range of topics they are learning.
The resource recommender aims to provide suggestions of learning resources to users using the app. Therefore, the overall goal of the recommender is to support the users in discovering information, which, in some cases, the user is not even aware of s/he is looking for. These recommendations are calculated based on the identified and extracted features indicative of learning activities. This includes user-based features such as user-resource relations (e.g., clicks on resources) as well as resource-based features such as resource popularity or resource topics. Specifically, the task of our recommender system is to provide a personalized list of 10 learning resources for a specific user.
The other tool within the focus of our interest was an analytics tool presenting a dashboard for teachers. This dashboard visualizes the students' activities (if students have accepted sharing their information with the teacher). Additionally, the teacher would see the aggregated data of the group (average), and the information of a specific student to be able to compare him/her with the group. The dashboard for teachers, which is based on the learner dashboard, was not developed by the time of the focus group II. Therefore the teachers saw the tools developed for learners and were told about the plans to release a further version for teachers with the previous additional features. In the session, a demo of both tools learner dashboard and recommender was presented, together with some functions developed in the mobile application. The objective of the application is to provide feedback to the learners on their learning activities in the various topics they are addressing, and to enable them to set learning goals and track their own learning activities. The main features of the mobile application are:

- Identification of user's learning scopes based on the visited topics.
- Learning dashboard that includes graphic visualizations:
    - Front-page with two sections: 1) learning scopes, with possibility of selecting one of them to see the activity in this topic; 2) general view of activity in the Didactalia games that showed games played by time spent, number of tries or score.
    - Visualization for a given scope, which presents: 1) the state of learning indicators for the scope (the defined indicators are: intensity, complexity, diversity, coverage); 2) identification of best time in the week in which the user has improved in every indicator; 3) recommended resources.
    - Visualization for a given game.
- Function to 'set goals' and track their evolution based on indicators, for example: increase work daily or increase coverage monthly.
- Integration of the recommender tool.

The mobile application has been integrated with the plugin 'browsing history', which registers the user activity on the internet, and into the Didactalia educational platform. Didactalia.net (the collection and core of Didactalia platform) is a large educational community based on semantics for students, teachers and parents, powered by GNOSS. At present, Didactalia's content collection has more than 100,000 education-

al resources from various sources and authors, as well as self-created content such as games (550, now in Geography and Anatomy) and lessons (400). Its registered users can create, share and discover educational content, and also promote learning communities and classes. In 2017 Didactalia had 12M sessions, 32M pages served, 350,000 members and more than 12M of educational plays (up to 150.000 plays/day).
In Focus group II, we presented the app version in Didactalia. The next figure presents some screenshots of the app

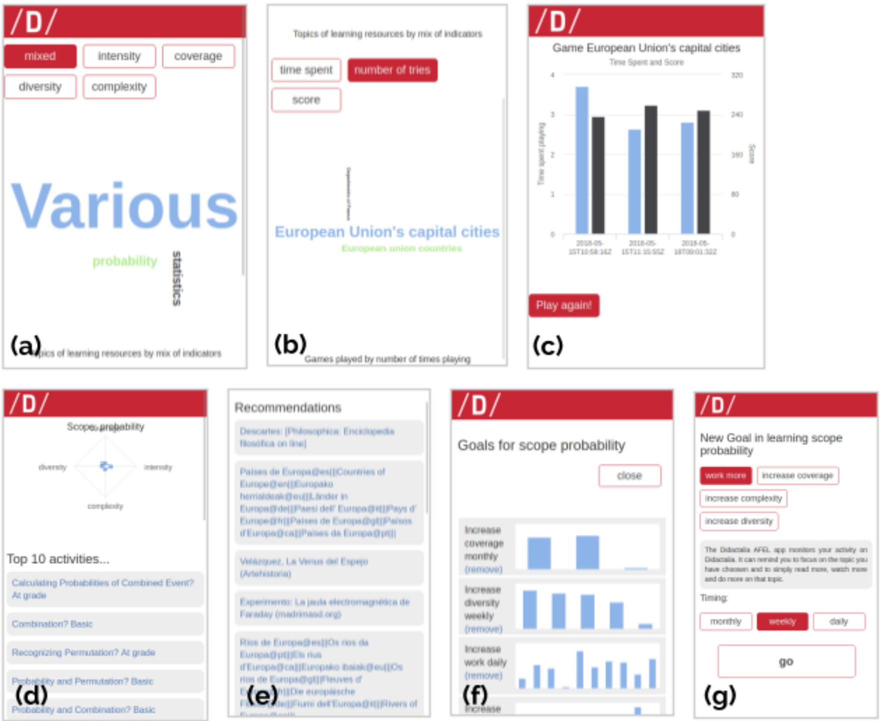

Figure 1: Screenshots of the AFEL mobile application, including front-page (a), part of the front-page showing games (b), visualization for a given game (c), visualization for a given scope (d), recommendations for a given scope (e), existing goals for a given scope (f) and setting of new goal for a given scope (g).

3.2 Research Goals

Altogether we conducted two focus groups, involving 15 participants. The first focus group (Focus group I) was conducted to get initial feedback about the resource recommender integrated in the mobile learning app. The goal was to answer the following research questions from the perspective of knowledge workers.

- RQ1: How does the learning resource recommender help you to improve your everyday learning?

- RQ2: Which indicators, measures or dimensions would be useful with regard to the defined improvements?

The goal of the second focus group (Focus group II) was to get the perspective of teachers for both tools, the dashboard and learning resource recommender and to answer the following research questions:

- RQ3: How/in which aspect do you think that the two tools would help you, as a teacher, to improve the teaching/learning process with your students?
- RQ4: Which indicators, measures or dimensions would be useful with regard to predefined clusters?

3.3 Focus Group I: Knowledge Workers

Participants: We recruited 9 knowledge workers (2 females, 7 males) using a voluntary snowball sampling approach for the focus group. The participants are active professionals and have backgrounds in computer science, engineering, controlling and human resources.
Focus Group: With the focus group, we addressed RQ1 and RQ2 stated above. Therefore, we divided the two hours into three parts: (i) a general introductory part to ensure that all participants are equally informed about the app and especially the learning resource recommender, (ii) *Round I* to infer improvements of learning with regard to the recommender (= RQ1) and (iii) *Round II* to derive indicators to measure the improvements (=RQ2).
At the beginning of the focus group, the participants were given an introduction to the related project in general and a more detailed introduction about the mobile app and its recommender, including a live demo. Then, the participants were asked to pose questions to eliminate uncertainties about the project and the app. Afterwards input from the participants was collected in two discussion rounds:
Round I: The goal of the first round was to identify potential application areas for analytics for everyday learning and specifically for the app and the recommender. To guide this exploratory brainstorming phase, the following four dimensions were written on a blackboard to serve as starting point for the discussion: Professional learning, competence development, private learning and learning management system. All participants were asked to write at least one application scenario and one expected improvement when using the app per topic on a post-it and put it on the blackboard giving a short explanation. The idea behind was to give every participant a voice and to reduce the influence of key actors in the group. Then the collected thoughts were thematically clustered in a moderated group discussion. Finally, the participants were asked to vote for their favorite clusters for the "gold" (1st place), "silver" (2nd place), and "bronze" (3rd place). This was done, to achieve convergence by collecting the final feedback and to get feedback on the importance.
Round II: The goal of the second round was to infer useful indicators for measuring the success of the app for the identified application scenarios and expected benefits. Thus, the participants were asked which indicators, measures or dimensions could be

used to assess the impact on the defined clusters. This time the participants were asked to write the indicators directly on the blackboard and to justify their proposal.

3.4 Focus Group II: Teachers

Participants: We recruited 6 teachers (3 females, 3 males) for the focus group. The participants are active teachers in different subjects: Spanish and Classical Languages, English, Mathematics and Physical Education.

Focus Group: With the focus group, we addressed RQ3 and RQ4 stated above. The focus group was carried out after focus group I and followed more or less the same procedure but with some deviations that will be described below. In the introductory part not only the project and the resource recommender were presented but also the dashboard for teachers / administrators were introduced.

Round I: This discussion round started with the clusters that emerged from the first discussion round of focus group I, with the following differences:

- The Cluster 'Personalization' was added, as we wanted to find out how teachers can personalize the activities with their students and to help them to learn better.
- We removed a cluster called "Social Learning" and we merged the "Evaluation/Certificate" cluster with the "Tracking" cluster.

Summing up, the initial clusters were: motivation, discovery, tracking, systemic/organization, learning goal and personalization. In this case all participants were asked to add at least one achievement per cluster. After the collection of thoughts, it was identified that 'evaluation' had an important role according to participant's opinion, thus it was added as a cluster and participants were asked to reassign their contributions considering this new cluster, if necessary. Afterwards again the same voting as in focus group I was conducted.

Round II: This round followed the same rules as the second round in focus group I.

4 Results

4.1 Focus Group I

RQ 1: Improvement of learning with the learning resource recommender

Round I: Altogether 37 expected achievements were put on the blackboard by the participants for the four initial topics. After having them sorted out thematically, the following clusters emerged with 3 to 9 improvements each: Motivation (5), Discovery (9), Tracking (4), Systemic (6), Feedback & Certificate (4), Social learning (6), Goal (3).

Motivation cluster: Participants assumed that the analytics for everyday learning and the app in particular will increase the motivation to learn. The cluster contains achievements like increasing and maintaining the motivation to learn as well as to have a tool that supports a learner in conducting regular learning activities, including the presentation to automatically presented reminders.

Discovery cluster: Participants stated that analytics for everyday learning and the app will support the discovery of suitable learning resources. The participants expect that users will get easier interdisciplinary views on a topic, make easier new connections between topics, get a quick and focused overview up to a quick orientation for new topics and find new sets of learning resources and improvement of learning cycles.
Tracking cluster: Participants expect that analytics for everyday learning and the app will support learners in tracking their own learning progress. This covers improvements regarding remembering resources, tracking the progress and making the learning path visible.
Systemic cluster: Participants expect that the analytics for everyday learning will systematize the informal learning and provide suitable guidance to the learners. Specifically, improvements like being more flexible in the learning schedule, getting a better organization for the learning process by becoming more systematic, getting a better focus on a topic and being able of multi-topic learning at one place are expected.
Feedback & Certificate cluster: The focus group participants expect that learners are more satisfied with the feedback in informal learning and that this could support certification of informal learning activities. In this regard improvements like the easy production of reports, the ability to support certification of informal learning processes and to make the learning visible and tangible, were discussed.
Social learning cluster: The participants expected that the app and specifically the recommender based on group data will increase social learning. Specifically, improvements in learning together across time zones and languages are expected and the app could serve as enabling factor that motivates to learn and to achieve something in the group. Also the gamification component was mentioned and the possibility to better reflect together on the learning and to expand learning experience of others.
Goal cluster: The participants expected that the app will support learners in defining their learning goals and tracking their status. Within the focus group concept-driven learning to set learning goals for informal learning was discussed.
After the clustering, the voting was conducted and the importance of the clusters was ranked as follows: Discovery (1st place), Social Learning (2nd place) and Goal (3rd place). A detailed voting results can be found in Table 1.

Table 1. Focus group I: Detailed voting results per cluster.

Cluster	Gold	Silver	Bronze
Discovery	7	1	
Social Learning	1	1	1
Goal	1		
Systemic		3	2
Motivation		2	5
Tracking		2	1
Certificate			

RQ2: Indicators for measuring the improvements

Round II: Based on the voting in the first round, we selected the four most relevant clusters for this round: motivation, discovery, goal and social learning cluster.

For the motivation, discovery and goal cluster, we received 2 indicators per cluster, for the social learning cluster we got 4 indicators as depicted in Table 2. The most relevant with respect to the recommender are the following two: usage of recommendation and the diversity indicator. The first indicator measures if the suggested recommendations are really used, while the second measures how participants refer to receiving recommendations from a diverse set of topics.

Table 2. Focus group I: Indicators for the four clusters motivation, discovery, goal and social learning.

Cluster	Indicator
Motivation	• Time of learning/the time spent as learning time • Quality of learning • Attitude towards learning • Achieved learning goals
Discovery	• Usage of Recommendation • Diversity Indicator
Goal	• Number of selected goals vs. achieved goals • Dropout rate
Social Learning	• Number of connected peers • Community of practice assignment • Number of shared resources • Number of communication

4.2 Focus Group II

RQ 3: Improvement of teaching/learning with the dashboard for teachers and learning resource recommender

Round I: Altogether 36 expected achievements were put by the participants on the blackboard to the 6 initial thematic clusters, that were reorganized in 7 clusters, when after the contributions 'Evaluation' was added. The following clusters organized the contributions with 3 to 7 achievements each: Motivation (6), Discovery (6), Tracking (4), Systemic/Organization (7), Evaluation/Feedback & Certificate (6), Learning Goal (3), and Personalization (4).

Motivation cluster: teachers agreed that the analytical tools will favor the motivation to learn. The achievements referred to: seeing one owns advances and how one can overcome objectives; comparison with other students finding out your strengths and weaknesses; the importance to perform searches of learning content connected with learning goals as an element of motivation. From the teacher's point of view, they mention that the tools could help them to encourage the pleasure of learning as learners feel motivated seeing their improvements, and students could be more motivated

with activities that are measured in the dashboard if it has an impact in the evaluation without the pressure of an exam. Gamification was also considered in this cluster.
Discovery cluster: as in the first focus group, participants thought that analytics for everyday learning and specially the recommender will support the discovery of suitable learning resources. They expressed that the recommendations could help to find activities related with the topic being studied and optimize the time dedicated for learning, to discover subtopics or new areas of interest and to select ‘extra’ or complementary contents based on the automatic suggestions. They also stated that the tools could help to know better the interests of the students and use this information to prepare the classes (connect activities, examples, etc. with the students’ interests).
Tracking cluster: most achievements expressed by participants were related to the evaluation of students’ work although they preferred to keep some of them in this cluster (evaluate the competence of ‘learning to learn’, the attitude, the time spent to achieve goals). One participant also mentioned that with these tools it could be possible to check if the workload is adequate.
Organization/systemic cluster: participants’ opinion was that analytics tools are potentially useful for the learner to organize oneself and for the teacher to organize work with students. The arguments they gave for this opinion is that the tools presented give information that can help students to optimize the time to learn (time spent, consider more and less productive hours…), to focus on the learning points to be improved based on progress shown in the dashboard, and to figure out if the student has understood the workflow.
Evaluation cluster: (equivalent to Feedback & Certificate): Participants agreed that analytics and the dashboard will support evaluation of students, and also self-evaluation helping to increase learner’s autonomy. They insisted again in the contribution to their evaluation without the pressure of the exam. They highlighted that it would allow to detect if the learner is focused or distracted from the learning goal or topic, and help to detect causes of diversion.
Learning Goal cluster: In relation to this cluster, the analytics tools and dashboard considered by the teachers of the focus group would help to go into detail in the learning goals, to reach a variety of contents, to measure comprehension and progress and to create interest to learn (not only to pass the exams).
Personalization cluster: participants expected that this kind of tools would improve personalized learning. On the one hand, it could be possible to personalize learning based on a better knowledge about own capacities and progress and, on the other hand, recommendations could be personalized (they talked about the model ‘resources seen by people with the same interests’). They also mention that it would be interesting to compare oneself with other users with the same interests as you and see their profiles (even anonymous profiles). From the point of view of the teacher, the tools would allow more precision in focusing on the content types.

After the clustering, the voting was conducted and the importance of the clusters according to these teachers’ view was ranked as follows: Systemic/Organization (1st place), Personalization (2nd place) and Motivation (3rd place). A detailed voting results can be found in Table 3.

Table 3. Focus group II: Detailed voting results per cluster.

Cluster	Gold	Silver	Bronze
Discovery		1	1
Learning Goal		1	
Systemic/Organization	3		
Motivation	1	1	1
Tracking		1	1
Evaluation (Certificate)		1	1
Personalization	2		

RQ4: Indicators for measuring the improvements

Round II: Similar to the focus group I, we asked the participants which indicators could be used in the defined clusters. Based on the voting in the first round, we selected the most relevant clusters for this round: organization, personalization and motivation. The discussion was also opened for other clusters. In this case, we did not use the blackboard and participants expressed their opinions directly. The contributions were not too precise to connect with a specific cluster or to define indicators, as they talked about what they suggested to be measured but not the indicator to do it.

5 Discussion

Our participants of both focus groups were positive about a tool supporting everyday learning and they supported our claim that analytics can support everyday learning. In this regard, learners expect that analytics for everyday learning will primary enhance the motivation to learn, the discovery of learning and the social learning. In addition, teachers expect advantages in organizing their work, improving self-organization by students/learners and in delivering personalized contents to learners.

Regarding the motivation, both groups expect that gamification is a major driver for enhancing the motivation to learn. Especially due to the visualization of different kinds of indicators, the learners can be motivated to try something new and to enhance the score. This is particularly boosted by the social learning component in which learners can compare their achievements with the achievements of their peers. Social learning, which has been proven to be very valuable for self-regulated learners, may not only help them to find peers with the same interest but may also be perceived as motivation to proceed with their learning through, for example, gamification or competition approaches [13]. Our findings in this regard are in-line with research on gamification in learning and supports our claim that analytics for everyday learning can enhance the motivation to learn.

Regarding the discovery, both groups expect (1) that the discovery of new learning materials will be easier for the learners and (2) that the learners will find new and different learning resources. Both are perceived as positive effects. The first effect reduces the cognitive load and time needed for search and the second effect broadens the scope of learning. The second effect is mainly expected due to the recommender which should deliver suitable learning resources. Hence, our participants support our claim that analytics for everyday learning make learning easier and broadens the scope of learning.

Regarding the organization of learning, teachers expect a reduction of workload and learners a better organization due to the definition of learning goals. For teachers the analysis of their classes is expected to provide better overviews about the learning progress and the learning goals of their students. This saves them time on the one hand but also enables them to provide more personalized teaching. The learners appreciate the setting of learning goals, as this allows them a better organization of their informal learning. In contrast to formal learning with its defined structures (i.e. curricula), providing such scaffolding structures in informal learning is particular relevant [13]. Hence, our interviewees supported our claim that analytics for everyday learning helps to organize and to systematize everyday learning.

6 Conclusion and Future Work

In our work, we conducted two focus groups exploring the effects of analytics for an everyday learning recommender and a dashboard. As a result, three main claims are developed: (1) analytics for everyday learning can enhance the motivation to learn, (2) analytics for everyday learning make learning easier and broadens the scope of learning, and (3) analytics for everyday learning gives information that can help to organize and to systematize everyday learning.

For future work, we plan to use the insights gained in the focus groups to evaluate and improve our tools, together with the results of other evaluation studies. For example, in case of the learning resource recommender, we will focus on providing a good tradeoff between diverse and topic-specific recommendations. Specifically, by providing topic-specific recommendations, we aim to support our first claim (i.e., enhancing the motivation to learn) and by providing more diverse recommendations, we aim to support our second claim (i.e., making learning easier by broaden the scope of learning). Finally, to support our third claim (i.e., helping to organize and systematize learning), we plan to add a filter functionality to our recommender system. This would allow the user to filter the recommended learning resources by topics (e.g., to only receive recommendation related to mathematics).

In the second study with teachers, we also wanted to collect some feedback for the further development plan of the application related to the teacher's dashboard and some additional functions for learners, which include the option to share activity with others, the visualization of aggregated data and comparison with own activity, as well as the visualization of students' activity (aggregated and filtered by individuals) by the teacher. In addition, we also wanted to identify how participants found current learning indicators, utilities and their presentation in the dashboard, as well as whether they considered that other additional analytics activity data would be desirable.

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