Towards effective learning analytics for higher education: returning meaningful dashboards to teachers.

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Abstract. This research investigates the value of learning analytics dashboards (LADs) for teachers in higher education. Common learning analytics indicators and features from previous research are included in a survey to examine their usefulness for teachers. Feedback from teachers on the design of the example features has been incorporated into a new conceptual dashboard design, presented in chapter six. The research findings indicate that the average group of teachers has little experience with using learning analytics nowadays. The respondents of this research rated result and content-related indicators as useful. Action-related indicators about student activities in a learning management system are considered useful, but questions arise about the value and accuracy of student activity data. Features that enable teachers to perceive which students might be at risk for failing the course and features that provide insights about how students interact with course materials are found useful.
Overall, the teachers from this study acknowledge the potential of learning analytics. Future learning analytics dashboards should contain more precise indicators about student performance and the comprehensibility of course materials. More research evidence on the role and effectiveness of learning analytics applications is needed to understand how LADs could be used successfully with respect to students' learning context and the learning design of a course. Clear strategies for collecting, presenting, and using learning analytics data are needed to ensure a high-value proposition for both teachers and students.

Keywords: Learning Analytics · Higher education · Data visualization · Teachers · Dashboards.

1 INTRODUCTION

Better insights into the students' learning process, resulting in targeted and timely feedback to students: that is one of the promises of learning analytics in higher education [11]. Tracing the learners' digital footsteps can lead to comprehensive data collections. Learning analytics could potentially help educational institutions making predictions about the quality of teaching materials, student engagement with the course resources, and identifying underperforming students in an early stage, ultimately resulting in improved education [11]. The promises of learning analytics (LA) sound exciting and could offer institutions many possibilities, but the question arises how institutions can use it successfully.

The term 'Learning Analytics' was first mentioned by Long and Siemens [51] in 2011. Learning analytics is a relatively new term in the educational landscape. Up till now, there is no universal definition for learning analytics [2]. One of the most popular definitions of learning analytics was also proposed in 2011 by Long and Siemens and adopted by the Society for Learning Analytics Research (SoLAR):

> "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" [51].

Papers related to learning analytics come from various research fields such as social sciences, education, and technology [21]. The emergence of learning analytics is somehow derived from other related analytics applications such as business intelligence, web analytics, recommender systems, and educational data mining [21]. Learning analytics received more attention during the last decade due to the increase in technology use in education. Online learning is expected to grow within the next years as technology advances [42]. Not only the rise of technology adoption and use in higher education underlies the increase of attention for learning analytics. Other, more specific factors contribute to the increased interest in learning analytics.

Big Data

The growing amount of data that is available often leads to the desire to create value from the data that has been collected. The term 'Big Data' can be characterized by the high volume, velocity, and variety of the information [16]. Big Data requires specific technologies and analytical methods to create value from the information [16]. Learning management systems (LMSs) such as Canvas [1], Blackboard [2] and Moodle [3] allow universities to create their own virtual learning environment. Instructors can create courses and upload content, whereas students participate in a course and access the materials and assignments. Most LMSs offer a variety of features within the platform. Popular LMSs such as

[1] https://www.instructure.com/canvas/
[2] https://www.blackboard.com/
[3] https://moodle.org/

Canvas can be extended by installing plugins. A learning management system captures large amounts and different types of data. The system log of an LMS can capture student activities within the platform such as browsing time, the number of clicks, and the log in times [18]. Also, personal information of a student is stored within the LMS, such as the profile and academic performance [18]. Educational institutions deal with increasingly large datasets and face the challenge of extracting value from their available big data.

Online learning

Previously, courses were restricted to lectures, physical objects, and instructions on the premise. The digital area enables teachers and students to use digital tools for educational purposes. Students showed interest in personalized support and notifications about their progress in a course [17]. The rise of online learning and the availability of open educational resources lead to the emergence of massive open online courses (MOOCs) [9]. Famous MOOCs like Coursera [4], EdX [5], and Udemy [6] offer thousands of paid and free online courses. Several universities and companies partnered up with MOOCs to provide online courses [9].

Online learning can offer benefits to both students and teachers. However, problems can occur by fully committing to online learning [21]. Due to the lack of contact with other students and teachers, students can experience problems such as a loss of motivation or guidance in the digital environment [21]. Also, teachers might lack digital tools to perceive the behavior and problems students experience [21]. Understanding and evaluating the participation of hundreds of students in an online course can become challenging [21].

Political concerns

Europe University Association (EUA) [7] represents more than 800 universities in Europe. One of the EUA's key activities is leading policy discussions about quality assurance of universities. University performance evaluations can include multiple indicators, such as student satisfaction and student learning [10]. While measuring student satisfaction can help to improve teaching methods, student learning can be used to provide feedback for improving teaching effectiveness [10]. Learning analytics can monitor student behavior in online courses and potentially offer new insights to improve the effectiveness of teaching [24].

Impact of COVID-19 on education

At the time of writing, the world is suffering from the pandemic COVID-19. While researchers are working overtime to develop a vaccine for the virus, and healthcare workers are taking care of all the patients entering the hospitals, most people with non-vital professions are obligated to work from home. Hence, any form of education is given remotely. Teachers have to give entire courses

[4] https://www.coursera.org/
[5] https://www.edx.org/
[6] https://www.udemy.com/
[7] https://eua.eu/

online, and students are more dependent than ever on using online learning environments.

UNESCO estimated that roughly 1.5 billion students could not go to schools and universities [3]. Over 91% of students worldwide are impacted by nationwide closures [3]. In the 'Education 2030 Incheon Declaration and Framework for Action' UNESCO stated that countries should provide alternative methods for children and students who are kept out of school [54]. Bridging programs recognized by the state should function as replacement programs to ensure flexible studying [54]. Flexible learning is applied in periods of educational disruption, especially in China [27]. By using technology to support teaching and learning processes, learners are more flexible to make choices about where, when, and how learning occurs [35].

It is unclear what the post-pandemic society will look like in terms of education. Microsoft expects a new normal due to the different restrictions and new patterns in the way people work [58]. The switch to entirely rely on online learning at this moment is necessary but has several limitations. Especially teachers have to find new ways to guide or help students in a particular course. Learning analytics could potentially help teachers by delivering reports about student behavior in a virtual learning environment [57]. In times of educational disruption, teachers could be assisted with tools to evaluate the learning behavior of students and take additional interventions if necessary.

1.1 Types of analytics

Learning analytics gained more attention in the last decade, but the concept of learning analytics is relatively broad and needs to be further defined. Initially, 'academic analytics' was used to describe the analysis of admission processes in higher education with business intelligence techniques [23]. Academic analytics aimed to create a better understanding of student enrollment and retention in the first year of a study [23]. Long and Siemens [51] further divided the area of educational data analytics by introducing the term 'learning analytics' for those types of analytics that are focussed on learners. Educational data mining (EDM) is another well-known term in the field of learning analytics. It has a particular focus on the development of data mining algorithms to predict and detect factors or patterns in a learning process [28]. Learning analytics is more focused on deploying the algorithms in integrated learning designs for stakeholders [28].

The concept of learning analytics can be further divided into multiple types. The Society for Learning Analytics Research (SOLAR) provides four main categories [1]. The first stage of learning analytics starts with providing descriptive reports to stakeholders. Descriptive analytics provides insight into the past. Examples of descriptive learning analytics include: student feedback gathered from surveys, data that describes the student's lifecycle, such as the enrolments, study support, and exams [1]. Diagnostic analytics is a more advanced form of analytics and aims to discover underlying patterns in the data. Examples of diagnostic learning analytics are the analysis of data to find key performance indicators and metrics to raise student engagement [1]. Predictive analytics aims to understand

the future better. Identifying underlying patterns in historical data and applying statistical models and algorithms makes it possible to capture relationships [1]. Predicting drop-out rates at universities is a common form of applying learning analytics [33]. The last and most advanced stage is prescriptive analytics. Prescriptive analytics can advise on possible outcomes. Prescriptive analytics differ from the other stages by recommending choices using machine learning, business rules, and other types of computational models [1].

1.2 Areas of learning analytics

Learning analytics aims to exploit the vast amounts of data that is nowadays available through online learning systems [21]. Recent work has provided an overview of the motivation for data collection and analysis by universities. Learning analytics addresses concerns related to both teaching and learning areas. Learning analytics aims to address the following areas of education; retention and student success [6][41], improvement of learning design, courses and teaching practices [18][12][22], personalized student support [40][12]. The full potential of learning analytics in addressing these various areas has not been reached. Much of the focus to date is related to improve retention and succes rates of students [60]. Learning analytics applications occur in many different forms. Examples of learning analytics initiatives include dashboards, recommender systems, predictive analytics, interventions, and alerts [60]. A sample learning analytics dashboard from the Open University including predictive analytics is presented in figure 1.

Fig. 1. OU Analyse dashboard from the Open University.

1.3 Aim of this research

This research aims to explore further the field of learning analytics applications for teachers. Dashboards are a common type of tool teachers can use to view the available analytics for a specific course. Learning dashboards are described as 'personal informatics' applications that support users to collect information about various aspects or interests [38]. In recent studies, learning analytics dashboards have been developed to support both teachers and learners [56]. Delivering useful dashboards to teachers requires the provision of useful information, displayed in an accurate way [7]. In a recent report from the SHEILA project, the researchers highlight the importance of LA tools to be easy to use and present useful information that would be beneficial for teachers [53]. Dashboards can consist of a wide range of visualizations about learning analytics data. Research addressing the usefulness of different visualizations and visual metaphors is limited [49].

An overview of current learning analytics dashboards (LADs) for teachers is needed to discover how LADs are used nowadays. After reviewing the current features and data in LADs, surveys are spread under teachers to investigate the teachers' beliefs on learning analytics dashboards by using examples from the literature. This research aims to contribute to the research area of learning analytics by providing research evidence on the perceptions of teachers about the usefulness of learning analytics dashboards for their teaching practices.

According to the aim of this research, the following research questions will be answered:

- RQ: To what extent can learning analytics dashboards assist teachers in their teaching practices?
- SQ1: To what extent do teachers use learning analytics nowadays?
- SQ2: What types of indicators and data do teachers use?
- SQ3: What types of learning analytics data and idicators are most useful according to teachers' beliefs?
- SQ4: In which ways can learning analytics dashboards be useful for teachers?

1.4 Scope of this research

This research has a particular focus on LADs and teachers in higher education. Schwendimann et al. [49] highlight the importance of research focussing on the evaluation of dashboards by understanding adoption and impact on learning. Due to time and resource constructions, this study is considered short-term research. Further delineating the research is necessary for more relevant results. Understanding the acceptance of learning analytics tools by teachers helps to provide a foundation for future LAD implementations. Learning analytics dashboards retrieve and present information from online learning environments about students' behavior and performance. This research aims to understand what indicators and features from learning managements systems about the learning process of students are relevant to present using dashboards. There is little evidence available about the usefulness of specific learning analytics features and

indicators for teachers. This study is considered an exploratory study as no direct, comparable studies have been found so far.

2 RELATED WORK

The Science for Policy report by the Joint Research Centre (JRC) provides evidence-based support to European policy-making processes [22]. The research highlights the gap between the supply and demand side of current work on learning analytics in Europe [22]. The demand side concentrates on the use of analytics tools by teachers, administrators, and students. Kennisnet[8] in the Netherlands is an example of an institution that mediates between IT vendors and primary or middle schools to ensure analytics products consist of useful features for the end-users. The limited evidence and formal validation of current learning analytics tools are related to the timeframe and the lack of long-term studies [22]. The report's inventory reveals that organizations are willing to invest time and resources to achieve evidence on learning analytics. A number of European countries are already rolling out nationwide approaches and infrastructures to support learning analytics initiatives [22]. Tools in the inventory mainly display data about learners through visualizations or by providing summaries or descriptions about the learners' data [22]. Learning analytics tools can be used for various purposes. Some tools from the inventory provide alerts about students that might need support. Other tools predict future performances or recommend resources to improve performances, whereas other analytics tools focus on assessment and designing interventions [22].

2.1 Actionable insights

Learning analytics tools can help teachers observe and understand the learning behavior of students. However, the subsequent actions of interpreting the analytics have a high impact on the effectiveness of LA [13]. Also, the structure of the course could impact the usefulness of the applied type of learning analytics [15]. For example, uploading the content of course materials directly to the LMS by spreading the content over multiple pages can help to retrieve more precise tracing data [15].

The availability of learning analytics data for teachers makes it possible to retrieve actionable insights about the learning process of students. Actionable insights can be described as insights which lead to subsequent actions [29]. The concept of actionable insights should not be misunderstood because the availability of data alone is not enough. The workflows or subsequent actions based on the data determine what constitutes as actionable insights [22]. Corrin et al. [15] state that teachers might need training or guidelines to understand the analytics dashboards and define thresholds for subsequent actions.

Many studies have demonstrated that learning analytics interventions can contribute positively to education in different forms [11]. However, few studies

[8] https://www.kennisnet.nl/

found negative consequences of learning analytics interventions. One study shows that students are more likely to stop with an elective course after receiving an intervention [34]. Another study found that students were less motivated after they received an intervention [41].

2.2 Teachers

Many proposals or concepts of learning analytics dashboards do not specify a target educational level and try to cover a wide range of users, which makes it hard to identify specific needs for different groups of teachers [49]. An analysis of 101 articles on learning analytics revealed the limited scalability of existing work [36]. The small group sizes of previous studies make it difficult to apply the results in a wider context.

Studies have shown that teachers are interested in the field of learning analytics [15] [59] [60]. However, several researchers state that despite the interest of teaching staff in learning analytics, they often have a limited understanding of the analytics that is currently available and how it can be utilized [15] [59]. Teaching staff members were more concerned about the broader context of students' performances and how analytics can improve teaching and learning [60]. Through multiple case studies, the researchers found that most of the questions teaching staff want to answer can be related to the 'descriptive' level [60]. Unsurprisingly, teachers were more likely to invest time and effort in analytics if the value proposition was clear. The study also highlights the variation in knowledge and skills in relation to the teachers' appreciation of LA reports. An issue that might be fatal for the adoption of learning analytics is the level of data literacy among teachers, which was mentioned by several teachers [15]. The level of data literacy can be explained as the ability to interpret the available data. Visualizations for teachers should be easy to understand and provide useful information [60].

3 LEARNING ANALYTICS DASHBOARDS

This section provides an overview of the indicators and features from existing learning analytics dashboards. The description and comparison among multiple LADs help to understand the current state of the art.

A recent literature review of Schwendimann et al. [49] provides an overview of research on learning analytics dashboards. Research on LADs aims to explore what data is relevant for various stakeholders and how learning analytics data can support sense-making processes [49]. The literature review included 55 articles and aimed to distinguish different kinds of researches [49]. Schwendimann et al. [49] identified multiple types of users in the reviewed papers. Teachers (75 percent), students (51 percent) were the primary users of the dashboards. Other users, such as administrators and researchers, were mentioned less frequently. The papers were also classified on the type of learning scenario. Formal learning, intentional learning provided by an educational institution, was mentioned in

91 percent of the papers. Some of the papers (31 percent) did not mention a specific educational level, whereas 51 percent of the papers mentioned university education [49].

3.1 Purpose

Learning analytics dashboards could help teachers perceive student behavior in an online learning system. Schwendimann et al. [49] discuss the purpose, indicators, and data sources used in learning analytics dashboards. The purposes of the reviewed dashboards were mapped into three groups: self-monitoring (51 percent), monitoring others (71 percent), and administrative monitoring (2 percent). Another review of learning dashboards by Park and Jo [43] highlighted the intended goals of learning analytics dashboards more specifically. Monitoring multiple students could help teachers in performing their job, such as providing feedback, evaluate performance, and grading [43].

3.2 Platforms

The learning analytics solutions mentioned in the papers relied on data from 51 distinct platforms [49]. Moodle was mentioned the most (18 percent) and other unidentified LMSs were mentioned in multiple papers (13 percent). Also external platforms processed data, such as Twitter, Wikis and blogging platforms. Most papers relied on data from one platform, and from those papers the majority only collected one type of data [49].

3.3 Data sources

The system log of the application is the main data source for the majority of dashboards [57] [49]. Most of the dashboards presented data from only one source [57]. [49]. Six types of data sources were identified [49], including system logs (85 percent), learning artifacts created by students (29 percent), direct information from the learners (13 percent), institutional database records (9 percent), and physical user activity (7 percent). In another analysis of dashboards, the application log gathered data for all learning analytics dashboards included in the review [57].

3.4 Indicators

Over 200 different indicators were identified by the literature review of Schwendimann et al. [49]. Most dashboards in the reviewed studies included indicators about individuals (85 percent). Just under half of the studies (45 percent) included indicators about classes. Some dashboards of the papers contained indicators about groups or pairs (15 percent). The researchers decided to categorize the 200 indicators into six groups:

1. Action-related: present information about the actions performed by the learner, often in aggregated forms.
2. Result-related: present information on the outcomes of a learner's activities.
3. Social-related: present the social interactions between learners.
4. Content-related: resent information about the content the learner interacted with or produced.
5. Context-related: present information where the learning took place.
6. Learner-related: present information to describe the learner's background.

Unfortunately, many papers did not specify the indicators used in the dashboard. The indicators mentioned above were often based on the illustrations of dashboards included in the reviewed papers [49]. Hence, making claims regarding the distribution of indicators was perceived as challenging by the researchers. Moreover, the researchers state that indicators might belong to more than one group [49]. Schwendimann et al. [49] do not mention how often the groups of indicators occur. Moreover, despite the short description and a few examples, no clear visual examples of dashboard indicators are presented in the literature review [49].

A recent study designed and implemented dashboards to support teachers' decision-making processes in an electronic assessment system [26]. The research had a particular focus on student authentication. The Key Performance Indicators (KPI) for their assessment dashboard belong to the action-related, content-related, and result-related categories [26]. Another analysis of sixteen learning dashboards provided an overview of data sources presented in LADs [57]. Noteworthy, some dashboards might be included in the analysis of Schwendimann et al. [49]. The analysis reveals that eleven dashboards are intended for teachers [57]. The data sources used in the dashboards for teachers consisted of:

- Resource use (9 times): number of page visits or read to estimate effort and provide awareness for teachers.
- Time spent (8 times): tracks time spent by students to provide feedback and identify students at-risk.
- Artifacts produced (8 times): resources created by students, includes blog posts, responses, request, and annotations.
- Exercise and test results (7 times): indicates the learning progress of students.
- Social interaction (7 times): visualizes student interaction on forums, chats, and blogs.

The data sources from the analysis of Verbert et al. [57] were presented in dashboards for teachers. The data sources listed above can be grouped into the indicator categories earlier defined by Schwendimann et al. [49]: action, result, social, and content. This research aims to explore further the usefulness of indicators that belong to action-related, result-related, social-related, and content-related categories. The indicator categories are shown in table 1. The indicators are described using examples that fit into the category. Some example indicators may

fit into multiple categories but are placed in the category they most likely belong to. The example indicators are based on previous research, and commercial dashboards already in use. Context and learner related indicators are not included in this research. The learner-related indicators mainly belong to student administration systems and the context indicators are considered not so relevant for higher education. Understanding which indicators are relevant to teachers will help to develop and evaluate future learning analytics dashboards. Teachers might prefer different indicators because of their experience with analytics, experience in teaching, or their background. Further exploring the requirements and expectations of learning analytics dashboards in the form of indicators is needed to present useful visualizations to teachers.

Category	**Examples**	**Included**
Action	Clicks per session, time per session, time spent on task, log-in times, number of file downloads, number of artifacts produced.	X
Result	Final grades, interim grades, quiz results, group performance, submission details.	X
Social	Forum posts, group interaction, direction of interaction, number of responses.	X
Content	Frequency of content views, number of videos watched, time spent on topic, sentiment of messages regarding content.	X
Context	Location of students, geographical location, position in classroom.	
Learner	Prior education, age, previous courses taken, entrance grade.	

Table 1. Overview of indicators

3.5 Features

LADs aimed at teachers can provide a wide range of features by utilizing different data mining techniques. A recent analysis of learning analytics applications in higher education reveals that techniques, such as prediction, the distillation of data for human interpretation, outlier detection, clustering, and social network analysis are frequently used in LA publications [36]. The techniques used in previous publications primarily provide descriptive, diagnostic, and predictive analytics. One of the most cited studies is Course Signals, which aimed to predict student success and present the information to students in a dashboard [6]. Other

dashboards such as eLAT [18] provide descriptive analytics to help teachers explore student interactivity with the LMS after or before specific events, such as lectures. Clustering student performance is another frequently used technique to visualize indicators for teachers [30]. More personalized interventions could be provided to students with the help of clustering techniques [30]. The OpenDLAs dashboard provides descriptive analytics about student participation on MOOC platforms in discussions and forums [14].

In Appendix A seven common learning analytics dashboard features are listed with references to previous research. The features are frequently mentioned in previous research and differ from each other because of the indicators used. Features such as predicting at-risk students are used for other purposes than features observing which course content is accessed the most. The seven LAD features will be examined during this research.

3.6 Evaluation

The evaluations presented in the papers reviewed by Schwendimann et al. [49] were unequally spread. The majority (58 percent) did not describe any form of evaluation. Overall, only 29 percent evaluated dashboards in practice. For example, the dashboard was presented to teachers and information was collected about their usage. In general, mixed-methods methodologies for evaluation were used most often. Questionnaires and interviews were found most popular. Most evaluations from the reviewed papers addressed general types of evaluations, such as usability, usefulness, and satisfaction. The purpose of the evaluation was often to improve the dashboard itself. Open issues of the evaluation of dashboards regard investigating particular requirements for user groups and investigating specific visualizations and visual metaphors to represent activities of learning and teaching [49]. Other issues concern the level of detail of the information displayed on dashboards and the application of appropriate visualization techniques to present learning analytics data.

4 METHODOLOGY

This section describes the research strategy to answer the research questions. SQ1 and SQ2 aim to understand the teachers' experience with analytics within educational settings. SQ3 and SQ4 examine the teachers' current beliefs about the features (Appendix A) and indicators (Table 1) derived from multiple analyses on LAD's. Exploring the teachers' requirements and beliefs about learning analytics dashboards helps researchers to understand what teachers expect from learning analytics and how LAD's can provide value to teachers.

4.1 Survey

A quantitative approach is chosen to analyze the results of a larger group of teachers. Within the research field of Information Systems (IS), quantitative

methods have been used more often to confirm or disprove existing theories or assumptions [55]. Also, studies that evaluated the learning analytics dashboard often used questionnaires to measure or understand aspects such as usability, usefulness, or satisfaction [49]. The survey will be spread to teachers by using the researcher's network. Fellow students, friends, and colleagues will be asked to forward an email of the researcher, including the link to the survey and a short description of the research. Also, teachers within the network of the researcher are approached directly via email.

In general, the survey can be divided into two sections: experience with using current analytics and beliefs about learning analytics. The first section provides information about the background of the teacher by asking relevant questions about their experience with analytics in educational settings. The questions about the teachers' experience are described as follows:

- Usage of LMS statistics after the course is finished
- Usage of LMS statistics during the course
- Usage of other types of analytics for teaching purposes
- Using interim tests during the course
- Using quizzes during the course
- Analyzing quiz or midterm results
- Approach students who are falling behind, based on data from the LMS

All questions consist of multiple choice answers to let teachers choose the frequency of usage. Teachers can also select that they do not use the analytics or tests at all. After each question in the experience section, an explanation is requested. The last question of the experience section aims to understand what indicators or types of data teachers use nowadays. The question includes multiple example indicators and allows teachers to add indicators themselves.

The previous chapter of this research discusses recent studies about LADs and elaborates on frequently used features and indicators in dashboards. The second part of the survey aims to examine the pre-selected features and indicators by providing examples to teachers. First, questions about specific learning analytics dashboard features (Appendix A) are asked by presenting an example visualization and description of the particular feature. Teachers determine whether they would like to have the feature for their teaching practices by choosing the relevancy on a five point Likert scale ranging from strongly disagree to strongly agree. For every feature a subsequent open question is asked about the design of the feature. These open questions are asked to understand the user-friendliness and usability of the visual representation of the feature, which ultimately helps to design proper LA features.

After completing seven questions about features, the indicators of table 1 are presented to teachers. Two questions are asked per category of indicators. The first question allows teachers to indicate how useful the category of indicators is to improve teaching practices and learning processes. Again, teachers can do so by choosing the relevancy on a Likert scale ranging from one to five. The second question enables teachers to select examples of indicators from the according category.

Finally, concluding general questions about learning analytics dashboards are asked to gain a better understanding of the teacher's beliefs. Questions are asked about the teacher's impression about using learning analytics, the confidence towards using LAD's, the level of detailed information the indicators present, and the effort of reviewing the analytics dashboards.

5 RESULTS

This chapter describes the results from the survey. First, a general description of the respondents is provided. Second, the respondents' answers to the experience-related questions are described. The third subsection describes the closed and open answers given to the example features questions. Next, the answers to the subsection of indicators are presented. Finally, the answers given to the concluding questions are described.

5.1 Respondents

The target group of the survey was aimed at teachers from higher educational settings. In total, the survey was filled in by 32 respondents. From this group, three respondents classified themselves as teacher assistants. The other group considered themselves as teachers. From the total group of teachers, 22 percent work for 0 to 5 years as a teacher, 31 percent work for 5-10 years as a teacher, 28 percent work for 10-20 years as a teacher, and 19 percent of the respondents work for more than 20 years as a teacher.

All respondents teach at universities or higher professional education institutions. Most of the respondents (26; 81 percent) teach at universities, and a few respondents teach at higher professional educations (5; 16 percent). One respondent did not specify any educational level or institution. Most teachers were approached within the network of the researcher or within the network of the researcher's acquaintances. This strategy resulted in a high number of respondents from Amsterdam universities. An overview of the distribution of the respondents across educational institutions in the Netherlands can be obtained from figure 2. The respondents were asked which department of the university they belong to. The network strategy for sending out the survey and the short duration of the study led to a large number of IT and business-related backgrounds of the respondents.

Several statistical tests, including the Kruskal Wallis and Anova test, have been carried out to investigate possible influences of the respondents' background on the closed questions. The averages between groups of the variables: year of experience, departments, and educational institution were examined for all of the closed questions of the survey. No significant differences between groups were found. However, the small number of respondents and unequal distribution of respondents among education institution and departments deprive the ability to perform meaningful statistical tests.

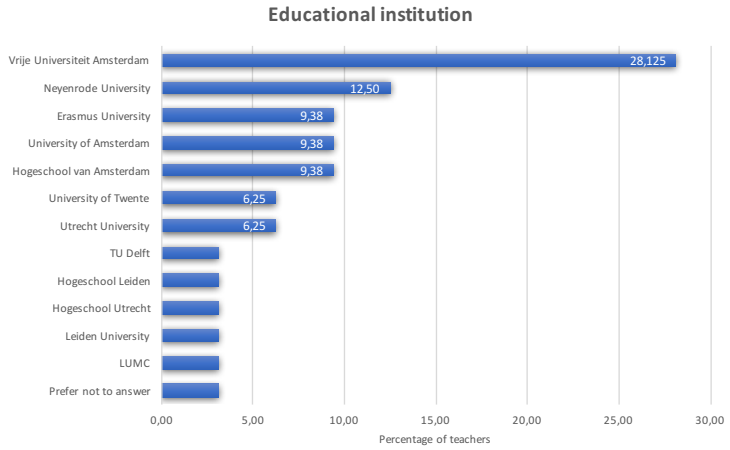

Fig. 2. Distribution of teachers among educational institutions.

5.2 Experience with analytics

Use of analytics

Figure 3 shows that 38 percent of the respondents did not use statistics from an LMS after the course was finished. Most of the teachers explained that they do not have access to the statistics, or they were not aware or unfamiliar with statistics from an LMS (5 out of 12). Other reasons for not using statistics of the LMS after the course were: "done by other staff members," "student data protection," "not needed," "analytics through separate or other systems," "insufficient time," and "unclear value." The same percentage of teachers (38 percent) did use statistics, but occasionally. A quarter of the participants used statistics from the LMS frequently (8 out of 32). Reasons for using the statistics included: "course evaluation," "understanding students," "provides additional insights," "In combination with other evaluation types (e.g., student evaluation surveys)," "understanding teaching effectiveness," "to improve education," and "to evaluate students' performance and experience."

Figure 3 provides information on the use of statistics from the LMS during the course. Less than half of the respondents (15 teachers; 47 percent) did not use statistics from the LMS during the course. Another large group of the respondents (14 teachers; 44 percent) did use analytics, but occasionally. Only three teachers used the statistics from an LMS every week (9,4 percent). Reasons for not using statistics during the course included: "gives limited insights in student progress," "the value is unclear," "I have insufficient time," "privacy regulations," "limited options or data," "not aware or no experience," "I prefer personal interaction," "not authorized," and "use of other systems." Reasons for using the statistics during the course included: "steering and monitoring stu-

dents," "gives more insights," "to ensure learning goals," "only used for specific questions," "understand student engagement and experience," "receive feedback for staff," and "evaluate students' work."

Overall, the results described above highlight that the average group of the respondents has little experience with using statistics provided by the LMS. Most frequently mentioned explanations for not using the statistics included the lack of time, unclear value and limited data available.

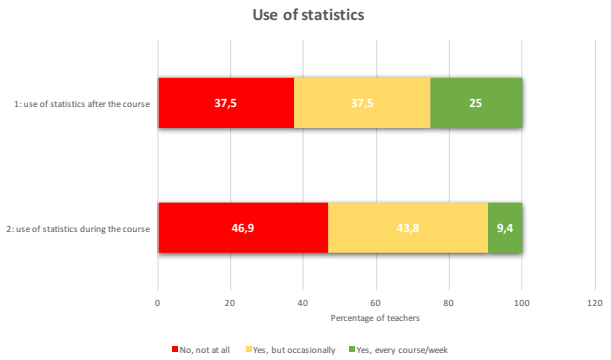

Fig. 3. Use of statistics during and after the course by teachers.

Other types of analytics used

Question 3 asked teachers about other types of analytics they use to improve teaching or learning activities. Most of the teachers (23 teachers; 72 percent) did use other types of analytics. Most teachers (14 out of 23) mentioned surveys as one of the primary types of analytics used to improve teaching or learning activities. Some teachers specified formal course evaluation surveys after the course is finished, others used surveys during the course. Direct forms of feedback from students, such as face-to-face conversations, class feedback, and student boards, were also mentioned multiple times. Other analytics teachers used included: quizzes or polls, test results or pass rates, and course material evaluation by students.

Quizzes and midterms

Figure 4 presents the outcomes of question 4a, 4b, and 4c. The results help to understand to what extent teachers use interim assessments to monitor student learning. Figure 4 presents that 28 percent of the teachers used quizzes during all their courses. Half of the teachers used quizzes in their courses occasionally. Seven teachers did not incorporate any quizzes in their courses. A small group of teachers incorporated midterms in their courses (25 percent). Thirty-four percent of the teachers included midterm tests in their courses on an occasional basis.

A large group of teachers (41 percent) did not use midterms in their courses. A considerable number of teachers always analyzed the results of quizzes or midterm tests (41 percent). Thirty-one percent of the teachers did analyze the results, but on an occasional basis. More than a quarter of the the teachers (9 teachers; 28 percent) did not analyze the results of quizzes or midterms.

The open answers given to question 4d provide the teachers' motivation for (not) analyzing the results of quizzes and/or midterm tests. Most teachers did not provide a clear motivation for not analyzing the results. Based on the motivations from the respondents, the purpose for analyzing the results can be distinguished into two groups: course evaluation after the course and understanding the student learning process. Course evaluation includes the evaluation of course topics, materials, and lectures. The student learning group includes measuring student involvement, and perceiving aggregated or individual results to review the progress of students. Overall, the survey results show that the respondents included quizzes more frequently than midterms in their courses. A large group of teachers analyzed the results after the test or quiz was completed.

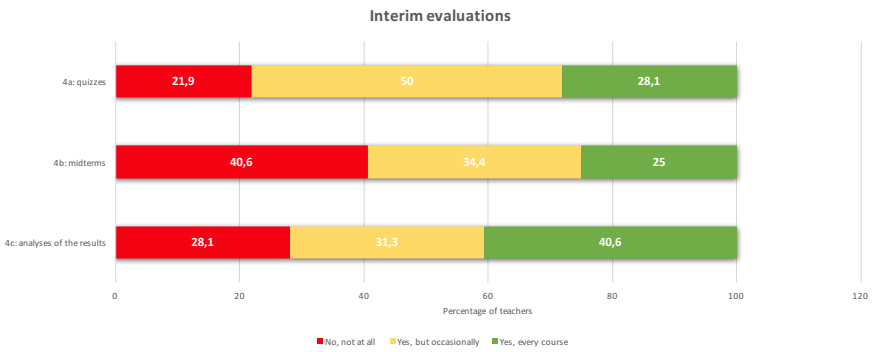

Fig. 4. Use of quizzes and midterms during the course.

Approaching students

Question 5 aimed to understand if teachers approach students based on the current online data that is available for them. The majority of the teachers (53 percent) did not approach students after observing the online data about students. Twenty-nine percent of the teachers did approach students occasionally. Few teachers (19 percent) always approached students based on the available online data. Teachers did not approach students for the following reasons: "done by other staff members," "student results are guiding for me," "student's responsibility," "too many students and time-consuming," "prefer face-to-face discussions," "no data available," and "only approached on attendance numbers." Teachers who did approach students gave multiple reasons: "to offer help," "ap-

proach students directly or with the help of assistants," "to improve students' results," "to adjust the course," "to identify barriers," and "to increase student retention rates."

Data or indicators used

Figure 5 presents the indicators or types of data teachers already used to understand the learning process and behavior of their students. Teachers had the opportunity to add options. The options contact with individual students, verbal tests, coaches, participation in class, and Remindo (statistical analysis program) were added once. The evaluation surveys, grade distributions, and assignment/quiz grades were selected by the majority of the respondents (respectively 75, 69, and 69 percent). Uploads in time was selected by 12 respondents (38 percent). The most frequently mentioned indicators from question 6 can be categorized as 'result-related' indicators from table 1.

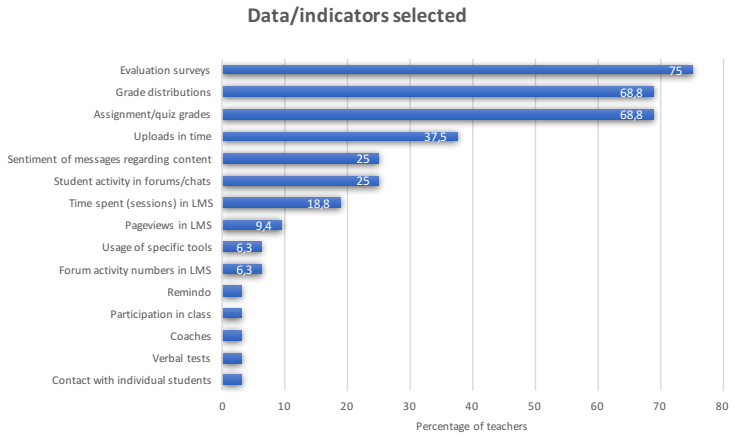

Fig. 5. Overview of the indicator or data types used by teachers.

5.3 Features

Multiple features were presented to teachers in the survey. Teachers indicated the level of relevance on a five point Likert scale, varying from strongly disagree to strongly agree. The results are presented in figure 6. The mean and median function as the measurements of the central tendency and determine which features were assessed best. Overall, only the usage of social platforms scored below a mean of 3.0 and is considered irrelevant for most teachers. Some teachers explained that "social activity numbers are not representative for understanding".

Most teachers preferred a dashboard feature were students are ranked by the degree of risk they face for failing the course. However, multiple teachers stated they "like to understand better why students are considered at-risk" to perceive more valuable insights. The feature 'accessed pages/materials in advance of certain events' scored a mean of 3,469 and a median of 4,0 and is also considered relevant for teachers. Understanding how students prepare in advance of lectures or assignments helped teachers to get additional insights in the student learning process. Some teachers preferred more aggregated results or other types of activities such as watching videos or performing tasks. The feature of question 11, which allows teachers to compare the results of students between groups, was also rated rather positive.

The other features from questions 7, 10, and 13 were also rated rather positive, but less prominent than the three features mentioned above. The value of an overview of student activity scored rather positive, but teachers stated that the feature only provides generic insights. The feature including the content access numbers also scored rather positive, but should be made graphical and provide insights about how many students viewed the materials and for how long.

The results of the experience section indicate the differences in approaching students between teachers. Multiple teachers stated that "students are responsible for their own performance". Besides, other teachers mentioned the large number of students in their course formed the main obstacle for approaching students. The feature representing an intervention feature scored relatively low. Teachers gave varying explanations, such as "not automated," check student context," "student's responsibility," and "such messages may be damaging for students." However, the positive scores for a feature that provides an overview of the students considered at-risk indicate that teachers believe such a feature could potentially be helpful.

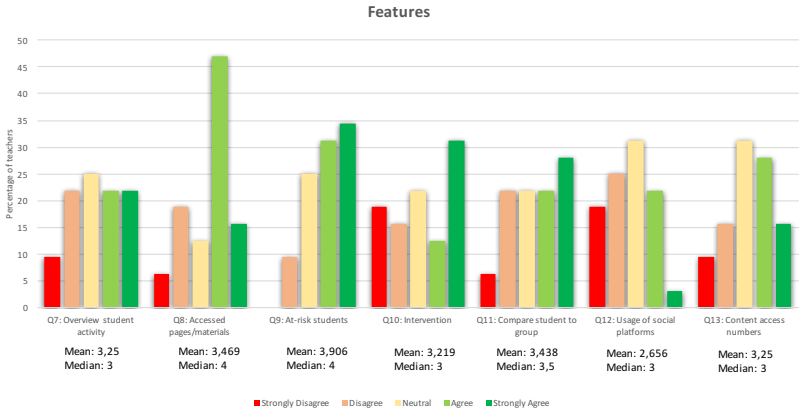

Fig. 6. Overview of the scores per feature.

5.4 Indicators

Result-related and content-related indicators were valued most relevant by teachers (Figure 7). Also, action-related indicators were rated positive. Social-related indicators are considered less relevant due to the slightly positive mean and the neutral (3) median. Result-related indicators helped teachers to understand the performance of the students and were therefore best rated. Content-related indicators were found helpful by teachers to understand how the content was viewed and when students interact with the content. Action-related indicators helped teachers to perceive general insights in the students' activities over a period of time, but the value of such information was not clear for some teachers.

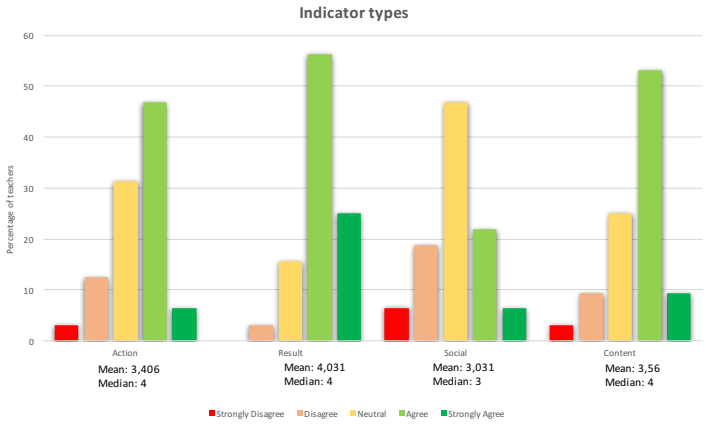

Fig. 7. Overview of the scores per type of indicators .

Selected indicators

The collected example indicators (Table 1) were presented to teachers in questions 14-18. The example indicators per group help to understand what data teachers find useful. The most frequently selected indicators are listed below:

- Action-related
  - "student activity over a period of time" (72 percent)
  - "time spent on a task" (53 percent)
- Result-related
  - "overview of student performance" (94 percent)
  - "student performance compared to average"(66 percent)
  - "quiz results" (66 percent)
  - "group performance" (50 percent)

- Social-related
  - “which students participate in the forum” (53 percent)
  - “interaction between students” (50 percent)
- Content-related
  - “time spent on a course topic” (53 percent)
  - “top accessed content” (50 percent)
  - “number of videos watched” (47 percent)

5.5 Final questions

The last questions of the survey measure the general beliefs of teachers about learning analytics. A majority of the teachers were convinced about the value of learning analytics for their jobs. Most teachers acknowledge the potential of learning analytics dashboards. ”Understanding students better,” ”identifying weaknesses of current practices,” and ”leveraging analytics to back up or disprove certain beliefs” were mentioned multiple times as the primary motivation. However, several teachers indicate the importance of observing the context of a student, the type of course, and the data available through the LMS as important aspects that have to be taken into account when using or designing learning analytics tools. Some teachers mentioned the privacy and ethics regulations that should be addressed before rolling out LA applications. Overall, most teachers were confident in using learning analytics. The teachers’ potential desires for more detailed indicators remain unclear. A number of open answers from the features section indicate that teachers prefer more detailed information about student’s behavior to understand their performance better. An overview of at-risk students should provide more detailed information why they are considered at-risk. The teachers’ perceptions on whether reviewing the analytics is considered a time consuming activity does not give a clear answer. Most teachers do not use the current statistics from their LMS regularly, so teachers might found it difficult to answer the question. On the other hand, teachers indicated multiple times the large number of students as the main reason for not approaching students. Reviewing the analytics should therefore not take much time for teachers, in order to incorporate the tool in their daily or weekly practices successfully.

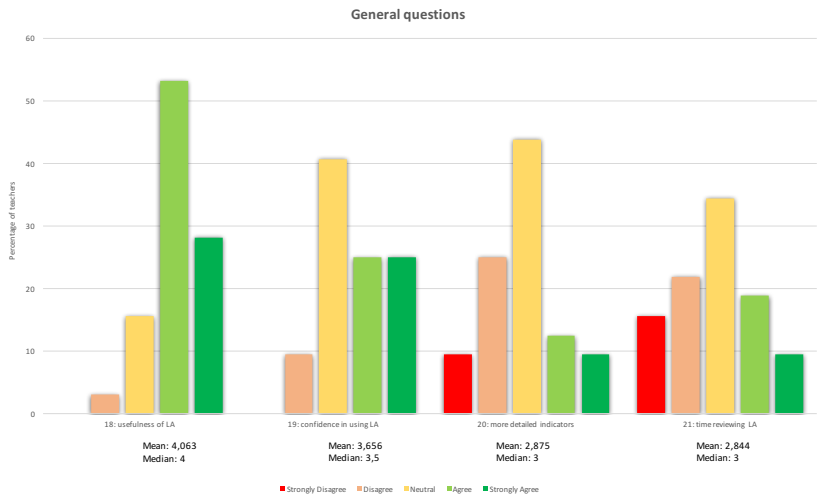

Fig. 8. Responses on final questions of the survey.

6 DASHBOARD CONCEPT

The results of this research are adopted in a learning analytics dashboard design. The LA dashboard design helps to visualize the main findings from the survey. The dashboard is designed using Figma. The proposed design consists of three web pages. The concept dashboard pages have not been evaluated by teachers. After the design was completed, a short interview was held with the CTO of SOWISO [9] to evaluate the usability of the design. The learning dashboard concept could be used in case studies about LA or as an example in the design phase of future LADs. The dashboard design is primarily based on the most valuable features and indicators that resulted from the survey. The design consist of result, content and action-related indicators. The first design presents the homepage. The second design is dedicated to result and action-related indicators about students. The last design presents features including content-related and action-related indicators about the course materials. The users should be able to manage the dashboard by adding or removing indicator blocks and features. Customization options can be useful when various staff members consult the analytics. Teacher assistants, study coaches, or administrators might prioritize other features.

6.1 Homepage

The first design shows the homepage of a learning analytics dashboard (Figure 9), including several features providing statistics about the course, such as the

[9] https://sowiso.nl/

student grades (2), student activity overview (1), and most viewed resources (3). A teacher should be able to observe the current state of the course quickly. The previous student activity feature (Appendix 12) is improved by using bar charts instead of line graphs. Moreover, the time spent is presented on the y-axis instead of the number of clicks (1). The previous top resources viewed feature (Appendix 18) is improved by displaying the frequencies visually.

Other potential indicators are depicted in the blocks above and underneath the features (8-13). These indicator blocks include: average grade (9), underperforming students (10), and percentage of finished assignments (11). The 'average time spent' was considered more interesting than the number of clicks or views, according to the teachers' answers from the survey. The indicator block 'average total hours spent' (13) presents a rough indication of the effort spent by students in the course. Also, the teachers' interest in outliers has been translated into the 'underperforming students' indicator block (10). The information icons depicted in the upper right corner of the blocks allow teachers to receive more detailed information on the indicator. The homepage functions as a landing page and should let teachers navigate to performance or content analytics pages.

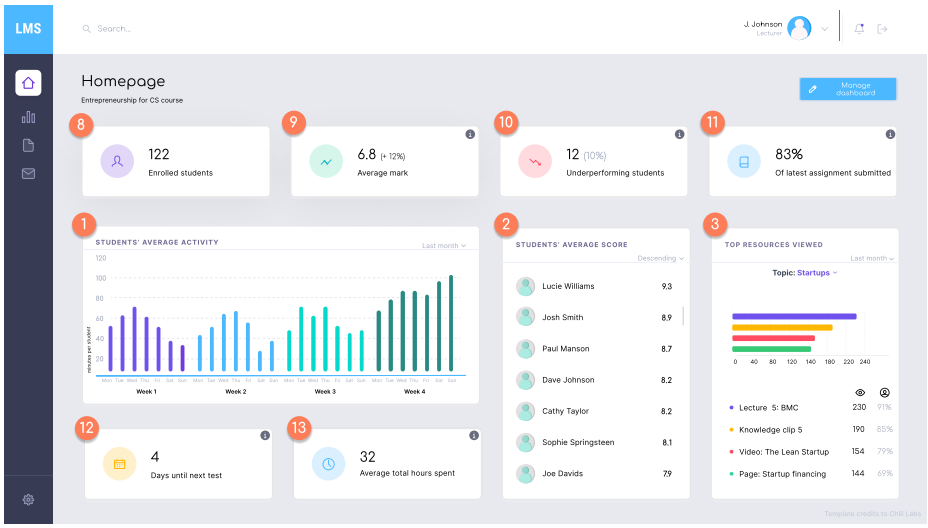

Fig. 9. Concept dashboard home page.

6.2 Performance page

The second design presents features and indicators which help teachers to understand how students perform during the course (Figure 10). Result and action-related indicators are presented. The first table (4) shows an overview of stu-

dents' performance, based on their grades and activities in the LMS. Teachers should be able to select each student and receive more details about why students are considered at-risk by the system. To perceive which students are classified at-risk, teachers from the survey desired more indicators and detailed information than presented in the feature from question 9 (Appendix 14). The performance and activities of the students over time should explain the calculation of the 'at-risk score'. Besides, notes from a study coach should also be made visible to avoid disregarding the student's context while intervening. The settings button above the table allows teachers to change the at-risk score variables or overwrite the risk score for a specific student. Multiple teachers mentioned that understanding the at-risk score and context of the student is important before sending an email or starting a conversation in class. An intervention can easily be performed by selecting the students and conducting an e-mail, for example. The table tabs allow the user to choose a more specific view. If the teachers are only interested in the grades of students, he or she could navigate to the grades table.

The bar chart next to the table (5) allows teachers to compare the performance or activities of a student to the actions or performance of the group. The bar chart shows the assignments and other selected variables of both the individual student and the average of the group. A teacher should be able to perceive how an individual performs compared to the group. The feature makes it easier for teachers to identify where students perform better or worse. The feature from question 11 (Appendix 16) is improved by processing the feedback from the respondents; using bars instead of line graphs and plotting the deviation from the average. Another included requirement is the legend next to the chart. Above the 'compare grades' feature a new indicator block presenting the average score for the latest assignment (14) is included. By clicking on the indicator block the teacher will be directed to the assignment's result page.

6.3 Course materials page

The third design provides the teacher with information about the course materials (Figure 11). The course access patterns feature (6) enables the teacher to select specific events, pages or documents, and a period. Understanding access patterns of the course materials or pages could help teachers understand the learning activity patterns of students better. The design of the feature from question 8 (Appendix 13) is improved by processing the feedback from the respondents; "highlight the specific event", "use spark-lines instead of pie charts", "add a legend presenting the percentage of students", and "include options to select particular materials". The average time spent per student this week (15) is included in the design and provides an indication of the activity level of students within the LMS.

Recommended feature

Multiple teachers mentioned they are interested in how well a course topic is understood or what kind of material students found difficult. Current features

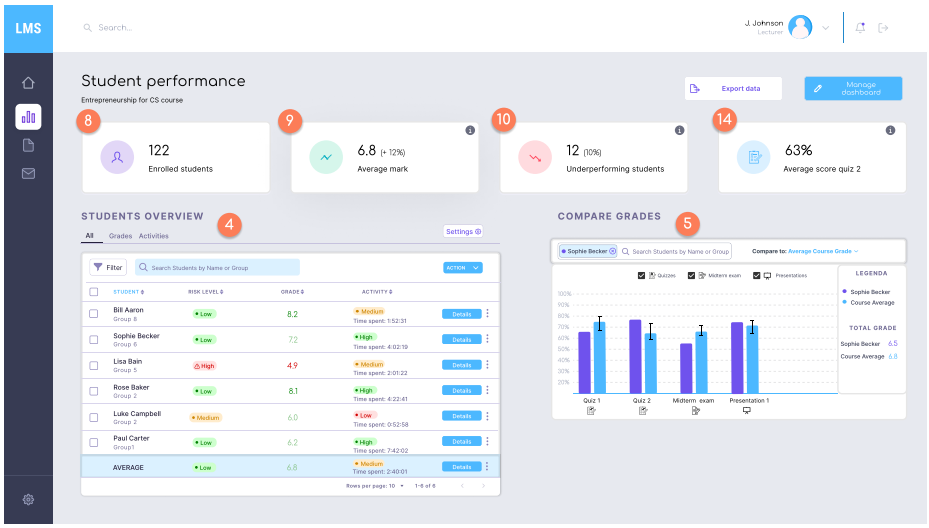

Fig. 10. Concept dashboard performance page.

including content and action-related indicators provide limited insights. The table next to the bar chart (7) shows the comments or questions by students plus a rating for the clarity of the page, structured per course topic. Integrating the comments and ratings in the course materials dashboard could be valuable for teachers to easily understand which materials students find difficult. The feature's design is based on the desire of teachers to see how well the course topics were understood. The indicator blocks (16-18) provide additional information on the comprehensibility of the course materials. Within the LMS, an additional plugin or application might be required to include rating and commenting possibilities at every course materials page. Embedding course materials in the LMS is another requirement to guarantee a high-value proposition of the feedback feature. Observing quickly how well a course topic is understood and which course materials need further explanation can give the teacher input for his or her lectures. Especially in times when education is given remotely, and face-to-face interaction is limited, gathering feedback from students can become difficult.

6.4 Time spent

Page views and access numbers were the main indicators for student activity in the features presented in the survey (Appendix B). Teachers frequently mentioned the value of page views and access numbers was not clear for them. Instead, the time spent on a task or page was considered more useful to represent student activity. One study examined the influence of several learning analytics variables on the final grade using a regression analysis [61]. The total study time significantly correlated with the final grade. The correlation between the login

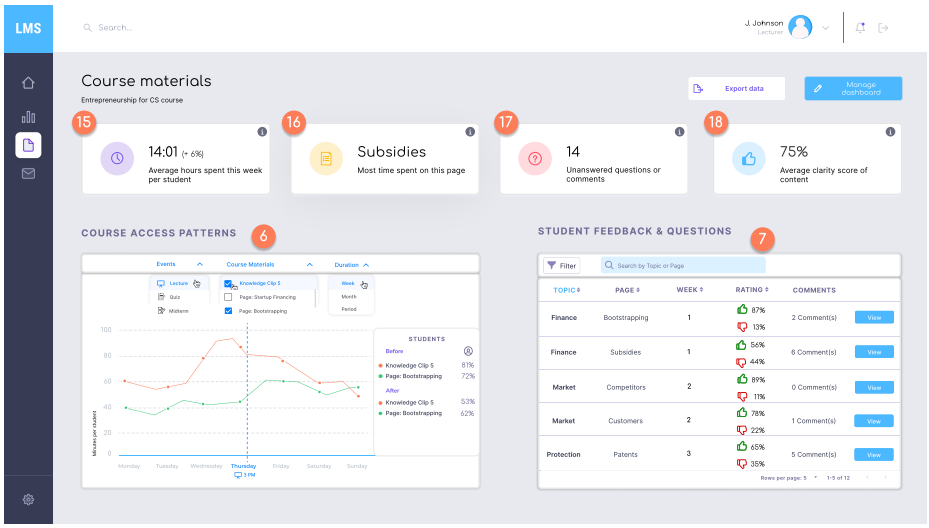

Fig. 11. Concept dashboard course materials page.

frequency in the LMS and the final grade was not found significant. The findings from another study over two experiments suggest that time-on-task estimation plays an import role in predicting the final grade of students [31]. These studies, combined with the respondents' feedback, encourage adopting the 'time spent' instead of page views in learning analytics dashboards.

7 DISCUSSION

7.1 Research limitations

The researcher recognizes several limitations of this study. The limited number of respondents, the uneven distribution of respondents among educational institutions and departments, the respondents' limited experience with learning analytics and the small number of features examined imposed limits on the degree of generalizability of the research results.

The results of this research are not representative of the total number of teachers in higher educational institutions in the Netherlands. However, the short-term period of this study and its exploratory nature set limitations on the number of participants for this research. Most teachers were approached through the network of the researcher which resulted in a large number of respondents from Amsterdam universities. Moreover, IT and business departments together represent the majority of the teachers. Statistical test were performed to discover potential differences between educational institutions, departments, teacher experience, and experience with using statistics from an LMS. No significant differences within these groups were found regarding the closed questions

of the survey. Further research is needed to examine the impact of a teachers' background on their beliefs about learning analytics applications. A group of respondents had no experience with analytics or statistics from an LMS, which could potentially make it harder for them to evaluate the usefulness of features and indicators presented in the survey. The scope and duration of the study set limits on the number of learning analytics features included in this study. A study from Fan and Yan [20] found a significant correlation between the size of the survey and the response rate. Different types of frequently used features were included in the survey. Other possible features have been disregarded to limit the size of the survey and focus on more common LA features, while not decreasing the response rate any further.

Another side note to make is that learning analytics dashboards itself do not increase student performance or teaching effectiveness. The interventions based on the analytics data determine the overall effectiveness of learning analytics applications [44]. This research does not examine interventions based on learning analytics. Future research should evaluate the impact of different types of LA interventions on the learner's performance and behavior.

7.2 Learning context

The usefulness of learning analytics could be dependend on the context in which learning activities occur, in terms of data collection and the ability or choice to act upon learning analytics data. Moreover, West et al. [60] conclude that the usefulness of LA visualizations or reports depend on the teacher's pedagogical approach and learning lifecycle. Multiple open answers provided by the respondents indicate the possible impact of the learning context on the usefulness of learning analytics applications. In the survey, teachers were not asked about what LMS their educational institution uses and what type of learning activities occur within the platform. However, some teachers did mention the learning context influences their beliefs about learning analytics.

One teacher mentioned that the various indicators he or she used do not come from the LMS, resulting in limited data collections. Another teacher explained learning analytics was not applicable for the course he or she teaches, because of the largely oral nature of the course. The respondent further explained that "there were hardly any quantities by which the student's efforts can be measured". Not only the type or nature of the course, also the setup of a course could influence the usefulness of learning analytics applications, which was also exposed by pilot studies of the Loop Tool [15]. If course materials or assignments are not shared within the LMS, the system can not trace student activities.

Various open answers from the survey show that teachers expect independence and responsibility from their students. The survey results show that many teachers did not approach students because they feel it is the student's responsibility to pass the course and the student should feel free to determine their own study rhythm. Before adopting learning analytics tools in teachers' daily or weekly practices, a consideration must be made to what extent teachers should approach students based on learning analytics data. Defining a clear strategy

based on the learning design first could help teachers to estimate the usefulness of learning analytics applications. As a few respondents stated: "some courses may have different staff members involved". Hence, determining who is reviewing the analytics and for which purpose can help staff members to use learning analytics applications in an effective way.

Descriptive and diagnostics analytics aim to provide insights into the past. The next stage of learning analytics focuses on predictive models that can be used for various purposes, such as predicting student performance. Predictive analytics require rich datasets of learning analytics data. Building rich datasets including survey data, formative assessments, and activity data could increase the value of learning analytics for both students and teachers [22]. Sharing learning analytics data between multiple systems might be required to retrieve useful analytics data. Tools like the Experience API (xAPI) [10] could help collecting LA data from multiple systems in a Learning Record Store (LRS). Educational institutions should plan early how to collect rich datasets and for what purposes predictive LA could be used.

7.3 Implications

This research contributes to the learning analytics research field by providing additional insights in the attitude of teachers towards learning analytics features and indicators. The research results could help stakeholders in their decision-making process by validating the usefulness of features and indicators in practice. Moreover, the proposed dashboard design could enable stakeholders to illustrate and evaluate LA features or indicators together with teachers in an early stage. The dashboard design could easily be transformed into a first working prototype. The results of this study suggest further research is necessary to examine the practical usefulness of the most valued features and indicators from this research. Instead of using the survey of this research, long-term experiments with LA or focus groups with teachers could deliver deeper insights in use cases for learning analytics. Measuring the expected impact of specific learning analytics tools could be performed by using the evaluation framework for LA designed by Scheffel [46]. The evaluation framework helps users to obtain a general indication of the overall quality of a LA tool, once it is developed. More research is needed to measure the effectiveness of learning analytics interventions with respect to the student's learning context.

[10] https://xapi.com/

8 CONCLUSION

SQ1: To what extent do teachers use learning analytics nowadays?

According to the results of the survey, the majority of the respondents had little or no experience with using the statistics from LMSs. A significant group of teachers used other types of analytics to evaluate the course. The majority of teachers used quizzes, occasionally or always, during the course. Multiple teachers explained that the interim tests' analysis helps them evaluate the course, check the progress of students, and raise awareness for students to understand where they are at. The research findings indicate that teachers do not use LA data frequently. Some teachers mentioned the LMS does not provide any statistics, other respondents explained they do not know where to find them or the value was not clear for them. Overall, the average experience of teachers using learning analytics nowadays is considered little.

SQ2: What types of indicators and data do teachers use?

This research examined the LA indicators presented in table 1. The indicators teachers used the most nowadays include: grade distributions, and assignment or quiz grades. The indicators teachers used mainly belong to the result-related indicators from table 1. Action, content, and social-related indicators were selected by a small minority. Typical tracing data, dedicated to action and social-related indicators, such as time spent and student activity in forums, were selected by a minority of the teachers. Also, content-related indicators such as 'pageviews in LMS' and 'sentiment of messages regarding content' were chosen by a small number of teachers. Evaluation surveys were mentioned by the majority of the respondents and aim to collect feedback from student for future quality improvements of the course. The limited experience of teachers with using statistics from an LMS and the unclear value proposition of reviewing the statistics can be seen as the most dominant factors for teachers to rely primarily on result-related indicators and evaluation surveys.

SQ3: What types of learning analytics data and indicators are most useful according to teachers' beliefs?

Result, content, and action-related indicators (Table 1) were valued the most by teachers. Result-related indicators were already frequently used by teachers, according to sub-question two. Content-related indicators could provide teachers with more insights into access patterns of the course materials. Action-related indicators were also considered relevant for understanding student activities within the LMS, but the value proposition for improving teaching or student learning was not clear for some teachers. Further research should examine the value of action-related indicators for improving teaching or student learning processes.

SQ4: In which ways can learning analytics dashboards be useful for teachers?

The research findings suggest that features or indicators that help teachers evaluate the performance of students and indicators about how students interact with the course materials were preferred the most. An overview of students

who are potentially at risk of failing the course could help teachers to approach students earlier. Some respondents preferred to have more detailed information about the student's context before planning an intervention. Access numbers about course pages or materials were found useful as a first insight, but do not represent how well the course content is understood. Indicators about the comprehensibility of course materials could be retrieved by implementing feedback or comment functions in the LMS. Some teachers suggested 'time spent' as a more useful indicator to represent student activity.

Before adopting learning analytics applications, educational institutions should evaluate which questions they want to answer with learning analytics and what data can be retrieved from one or multiple learning environments. Moreover, teachers should consider to what extent the available learning analytics data can represent the student's learning context in their courses.

RQ: To what extent can learning analytics dashboards assist teachers in their teaching practices?

Overall, the vast majority of the teachers acknowledge the potential of learning analytics dahsboard to help them improve their teaching practices and students' learning process. The respondents of this research indicate that learning analytics dashboards could provide teachers with additional insights into the learning process of students. Teachers preferred features and indicators related to the results of students and the comprehensibility of the course content. Action-related indicators such as "time-spent" and "number of page views" were also rated rather positive, but multiple teachers stated that the value remains unclear.

Thus, learning analytics dashboards could provide teachers with new insights about the student's learning process and the quality of the course. This research highlights the need for well-designed dashboards, including more detailed indicators about the performance of students and the comprehensibility of the course content. Rich datasets about learners are required to generate useful reports. More research is needed to increase the value proposition of LA and the accurateness of the data representing the student's learning process. Bringing analytics in a contextualized format is another challenge, taking the context of both the learner and the type of the course into account.

References

1. What is learning analytics?, https://www.solaresearch.org/about/what-is-learning-analytics/
2. What are learning analytics? - lace - learning analytics community exchange (Dec 2014), http://www.laceproject.eu/faqs/learning-analytics/
3. Covid-19 educational disruption and response (Apr 2020), https://en.unesco.org/covid19/educationresponse/
4. Alhadad, S.: Customised blackboard analytics, https://iru.knack.com/national-innovation-case-study-collection/
5. Ali, L., Asadi, M., Gašević, D., Jovanović, J., Hatala, M.: Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. Computers & Education **62**, 130–148 (2013)
6. Arnold, K.E., Pistilli, M.D.: Course signals at purdue: Using learning analytics to increase student success. In: Proceedings of the 2nd international conference on learning analytics and knowledge. pp. 267–270 (2012)
7. Baker, B.M.: A conceptual framework for making knowledge actionable through capital formation. Ph.D. thesis, University of Maryland University College (2007)
8. Bakharia, A., Dawson, S.: Snapp: a bird's-eye view of temporal participant interaction. In: Proceedings of the 1st international conference on learning analytics and knowledge. pp. 168–173 (2011)
9. Bali, M.: Mooc pedagogy: Gleaning good practice from existing moocs. Journal of Online Learning and Teaching **10**(1), 44 (2014)
10. Bedggood, R.E., Donovan, J.D.: University performance evaluations: what are we really measuring? Studies in Higher Education **37**(7), 825–842 (2012)
11. Van den Bogaard, M., Drachsler, H., Duisterwinkel, H., Knobbout, J., Manderveld, J., Wit, M.: Report learning analytics in education design: a guide (04 2016)
12. Broos, T., Peeters, L., Verbert, K., Van Soom, C., Langie, G., De Laet, T.: Dashboard for actionable feedback on learning skills: Scalability and usefulness. In: International Conference on Learning and Collaboration Technologies. pp. 229–241. Springer (2017)
13. Clow, D.: The learning analytics cycle: closing the loop effectively. In: Proceedings of the 2nd international conference on learning analytics and knowledge. pp. 134–138 (2012)
14. Cobos, R., Gil, S., Lareo, A., Vargas, F.A.: Open-dlas: an open dashboard for learning analytics. In: Proceedings of the third (2016) ACM conference on learning@scale. pp. 265–268 (2016)
15. Corrin, L., De Barba, P., Lockyear, L., Gašević, D., Williams, D., Dawson, S., Mulder, R., Copeland, S., Bakharia, A.: Completing the loop: Returning meaningful learning analytic data to teachers (2016)
16. De Mauro, A., Greco, M., Grimaldi, M.: A formal definition of big data based on its essential features. Library Review (2016)
17. Department, S.R.: Student interest in academic performance analytics 2015 (Dec 2015), https://www.statista.com/statistics/548097/student-interest-academic-performance-analytics/
18. Dyckhoff, A.L., Zielke, D., Bültmann, M., Chatti, M.A., Schroeder, U.: Design and implementation of a learning analytics toolkit for teachers. Journal of Educational Technology & Society **15**(3), 58–76 (2012)
19. Essa, A., Ayad, H.: Student success system: risk analytics and data visualization using ensembles of predictive models. In: Proceedings of the 2nd international conference on learning analytics and knowledge. pp. 158–161 (2012)

20. Fan, W., Yan, Z.: Factors affecting response rates of the web survey: A systematic review. Computers in human behavior **26**(2), 132–139 (2010)
21. Ferguson, R.: Learning analytics: drivers, developments and challenges. International Journal of Technology Enhanced Learning **4**(5/6), 304–317 (2012)
22. Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., Ullmann, T., Vuorikari, R.: Research evidence on the use of learning analytics: Implications for education policy (2016)
23. Goldstein, P.J., Katz, R.N.: Academic analytics: The uses of management information and technology in higher education, vol. 8. Educause (2005)
24. Greller, W., Drachsler, H.: Translating learning into numbers: A generic framework for learning analytics. Journal of Educational Technology & Society **15**(3), 42–57 (2012)
25. Hecking, T., Ziebarth, S., Hoppe, H.U.: Analysis of dynamic resource access patterns in a blended learning course. In: Proceedings of the Fourth International Conference on Learning Analytics and Knowledge. pp. 173–182 (2014)
26. Hormigo, I.G., Rodríguez, M.E., Baró, X.: Design and implementation of dashboards to support teachers decision-making process in e-assessment systems. In: Engineering Data-Driven Adaptive Trust-based e-Assessment Systems, pp. 109–132. Springer (2020)
27. Huang, R., Liu, D., Tlili, A., Yang, J., Wang, H., et al.: Handbook on facilitating flexible learning during educational disruption: The chinese experience in maintaining undisrupted learning in covid-19 outbreak
28. Jivet, I., Scheffel, M., Specht, M., Drachsler, H.: License to evaluate: Preparing learning analytics dashboards for educational practice. In: Proceedings of the 8th International Conference on Learning Analytics and Knowledge. pp. 31–40 (2018)
29. Jørnø, R.L., Gynther, K.: What constitutes an" actionable insight" in learning analytics?. Journal of Learning Analytics **5**(3), 198–221 (2018)
30. Kim, J., Jo, I.H., Park, Y.: Effects of learning analytics dashboard: analyzing the relations among dashboard utilization, satisfaction, and learning achievement. Asia Pacific Education Review **17**(1), 13–24 (2016)
31. Kovanovic, V., Gašević, D., Dawson, S., Joksimovic, S., Baker, R.: Does time-on-task estimation matter? implications on validity of learning analytics findings. Journal of Learning Analytics **2**(3), 81–110 (2015)
32. Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z., Wolff, A.: Ou analyse: analysing at-risk students at the open university. Learning Analytics Review pp. 1–16 (2015)
33. Larrabee Sønderlund, A., Hughes, E., Smith, J.: The efficacy of learning analytics interventions in higher education: A systematic review. British Journal of Educational Technology **50**(5), 2594–2618 (2019)
34. Lauría, E.J., Moody, E.W., Jayaprakash, S.M., Jonnalagadda, N., Baron, J.D.: Open academic analytics initiative: initial research findings. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge. pp. 150–154 (2013)
35. Lee, M., McLoughlin, C.: Beyond distance and time constraints: Applying social networking tools and web 2.0 approaches in distance education. In: Emerging technologies in distance education, pp. 61–87. Athabasca University Press (2010)
36. Leitner, P., Khalil, M., Ebner, M.: Learning analytics in higher education—a literature review. In: Learning analytics: Fundaments, applications, and trends, pp. 1–23. Springer (2017)

37. Leony, D., Pardo, A., de la Fuente Valentín, L., de Castro, D.S., Kloos, C.D.: Glass: a learning analytics visualization tool. In: Proceedings of the 2nd international conference on learning analytics and knowledge. pp. 162–163 (2012)
38. Li, I., Dey, A., Forlizzi, J., Höök, K., Medynskiy, Y.: Personal informatics and hci: design, theory, and social implications. In: CHI'11 Extended Abstracts on Human Factors in Computing Systems, pp. 2417–2420 (2011)
39. Liu, D.Y.T., Atif, A., Froissard, J.C., Richards, D.: An enhanced learning analytics plugin for moodle: student engagement and personalised intervention. In: ASCILITE 2015-Australasian Society for Computers in Learning and Tertiary Education, Conference Proceedings (2019)
40. Liu, D.Y.T., Bartimote-Aufflick, K., Pardo, A., Bridgeman, A.J.: Data-driven personalization of student learning support in higher education. In: Learning analytics: Fundaments, applications, and trends, pp. 143–169. Springer (2017)
41. Lonn, S., Aguilar, S.J., Teasley, S.D.: Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. Computers in Human Behavior **47**, 90–97 (2015)
42. Pappas, C.: Top learning management system statistics for 2020 (Nov 2019), `https://elearningindustry.com/top-learning-management-system-lms-statistics-for-2020-infographic`
43. Park, Y., Jo, I.H.: Development of the learning analytics dashboard to support students' learning performance. Journal of Universal Computer Science **21**(1), 110 (2015)
44. Rienties, B., Cross, S., Zdrahal, Z.: Implementing a learning analytics intervention and evaluation framework: What works? In: Big data and learning analytics in higher education, pp. 147–166. Springer (2017)
45. Santos, J.L., Govaerts, S., Verbert, K., Duval, E.: Goal-oriented visualizations of activity tracking: a case study with engineering students. In: Proceedings of the 2nd international conference on learning analytics and knowledge. pp. 143–152 (2012)
46. Scheffel, M.: The evaluation framework for learning analytics. Open Universiteit Heerlen, The Netherlands (2017)
47. Scheffel, M., Niemann, K., Leony, D., Pardo, A., Schmitz, H.C., Wolpers, M., Kloos, C.D.: Key action extraction for learning analytics. In: European Conference on Technology Enhanced Learning. pp. 320–333. Springer (2012)
48. Scheu, O., Zinn, C.: How did the e-learning session go? the student inspector. In: 13th International Conference on Artificial Intelligence and Education (AIED 2007). IOS Press (2007)
49. Schwendimann, B.A., Rodriguez-Triana, M.J., Vozniuk, A., Prieto, L.P., Boroujeni, M.S., Holzer, A., Gillet, D., Dillenbourg, P.: Perceiving learning at a glance: A systematic literature review of learning dashboard research. IEEE Transactions on Learning Technologies **10**(1), 30–41 (2016)
50. Searle, B., West, D.: Supporting learning analytics at cdu, `https://iru.knack.com/national-innovation-case-study-collection/`
51. Siemens, G., Long, P.: Penetrating the fog: Analytics in learning and education. EDUCAUSE review **46**(5), 30 (2011)
52. Smith, V.C., Lange, A., Huston, D.R.: Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. Journal of Asynchronous Learning Networks **16**(3), 51–61 (2012)
53. Tsai, Y.S., Gašević, D., Whitelock-Wainwright, A., Muñoz-Merino, P.J., Moreno-Marcos, P.M., Fernández, A.R., Kloos, C.D., Scheffel, M., Jivet, I., Drachsler, H.,

et al.: Sheila: Supporting higher education to intergrade learning analytics research report. SHEILA Project **30** (2018)
54. United Nations Educational, S., Organization, C.: Education 2030: incheon declaration and framework for action for the implementation of sustainable development goal 4 (2016)
55. Venkatesh, V., Brown, S.A., Bala, H.: Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. MIS quarterly pp. 21–54 (2013)
56. Verbert, K., Duval, E., Klerkx, J., Govaerts, S., Santos, J.L.: Learning analytics dashboard applications. American Behavioral Scientist **57**(10), 1500–1509 (2013)
57. Verbert, K., Govaerts, S., Duval, E., Santos, J.L., Van Assche, F., Parra, G., Klerkx, J.: Learning dashboards: an overview and future research opportunities. Personal and Ubiquitous Computing **18**(6), 1499–1514 (2014)
58. Warren, T.: Microsoft thinks coronavirus will forever change the way we work and learn (Apr 2020), `https://www.theverge.com/2020/4/9/21214314/microsoft-teams-usage-coronavirus-pandemic-work-habit-change`
59. West, D., Heath, D., Huijser, H., Lizzio, A., Toohey, D., Miles, C., Searle, B., Bronnimann, J.: Learning analytics: Assisting universities with student retention (2015)
60. West, D., Luzeckyj, A., Searle, Toohey, D., Price: The Use of Learning Analytics to Support Improvements in Teaching Practice (04 2018)
61. Yu, T., Jo, I.H.: Educational technology approach toward learning analytics: Relationship between student online behavior and learning performance in higher education. In: Proceedings of the fourth international conference on learning analytics and knowledge. pp. 269–270 (2014)

9 APPENDIX

A Dashboards features

Features	**Student activity over a period of time**	**Activity in advance of certain event**	**At-risk student detection**	**Intervention on performance**	**Compare between groups or individuals**	**Social network analysis**	**Accessed content**
Indicators	Action	Action, Content, Social	Result, Action	Result, Action	Result, Action, Social, Content	Social	Content
Corrin et al., 2016	X	X					
Dyckhoff et al., 2012	X	X					
Kuzilek et al., 2015	X		X				
Leony et al., 2012	X				X		
Park & Jo, 2015	X						
Scheu & Zinn, 2007	X						X
Santos et al., 2012	X						X
Ali et al., 2013	X						
Arnold & Pistilli, 2012			X				
Smith, Lange & Huston, 2012			X	X			
Essa & Ayad, 2012			X				
Rienties, Cross & Zdrahal, 2017				X			
Liu et al., 2019				X			
Scheffel et al., 2012					X		X
Kim, Jo & Park, 2016					X		
Bakharia & Dawson, 2011						X	
Hecking, Ziebarth & Hoppe						X	
Cobos et al., 2016						X	

B Survey features

B.1 Overview of course activity

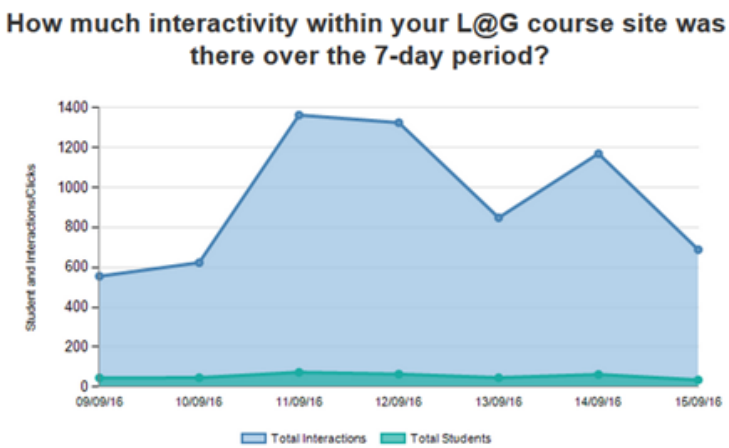

Fig. 12. Activity dashboard from a case study of Griffith University [4]

B.2 Access patterns before/after specific events

Fig. 13. Page views dashboard from The Loop Tool [15]

B.3 Identify at-risk students

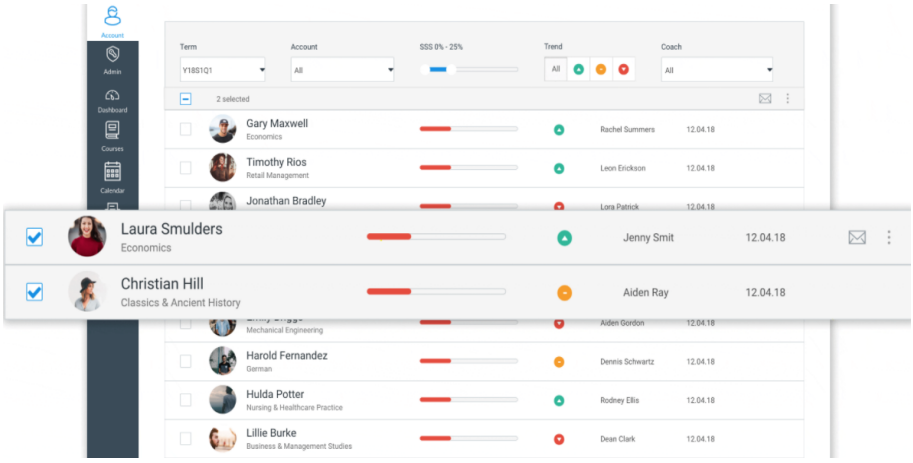

Fig. 14. Student analytics dashboard from https://Drieam.com/studycoach

B.4 Intervention message

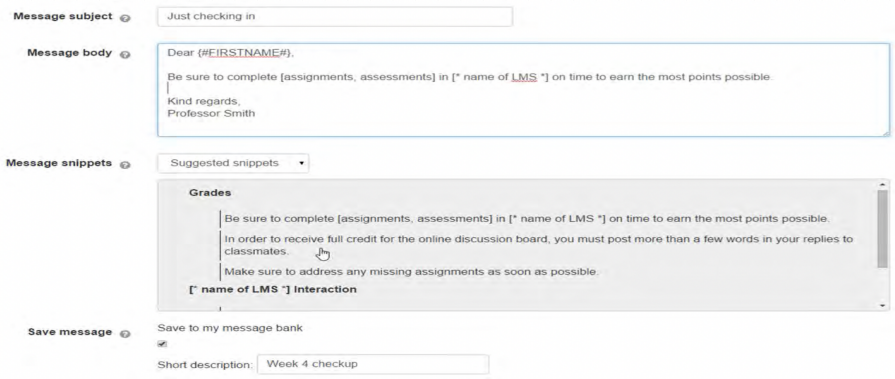

Fig. 15. Intervention message from Moodle Engagement Analytics Plugin [39]

B.5 Compare students

Fig. 16. Comparison feature from a caste study of Charles Darwin University [50]

B.6 Usage of social platforms

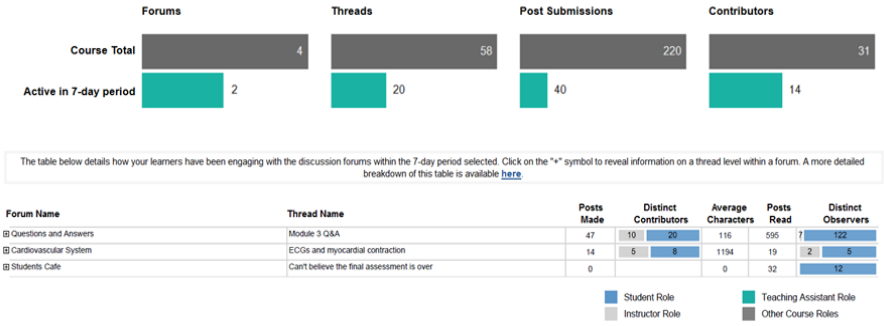

Fig. 17. Social analytics dashboard from a case study of Griffith University [4]

B.7 Course content

Top Accessed Content

Page	Type	Student Visits	Pageviews
Week 1 Lecture Notes	resource/x-bb-folder	406	7529
Neural Integration Online Modules (Lectures 6 - 10)	resource/x-bb-folder	404	4535
Diffusion, Osmolarity & Tonicity Onine Modules (Lecture 6 part)	resource/x-bb-folder	404	4451
Skeletal Muscle Online Modules (Lectures 11, 13, 14)	resource/x-bb-folder	402	3679
--TOP--	resource/x-bb-folder	409	3620
Lecture 1: Introduction, Homeostasis and Control Systems-1	resource/x-bb-document	400	2071
Lecture 5: Embryological origins of anatomical structures 2	resource/x-bb-document	397	2045
Lecture 2: Nervous system & nerves 1	resource/x-bb-document	401	2044
Lecture 4: Embryological origins of anatomical structures 1	resource/x-bb-document	399	2034

Fig. 18. Course content analytics from The Loop Tool [15]

C Survey

Template: `https://docs.google.com/forms/d/1pwLUBZGgPAv85Rhws2LXTs9ZGshKvTcHaa_kleTnEYc/edit?usp=sharing`

Responses sheet: `https://darylz.stackstorage.com/s/hMlNZRAFSjSwltf`