Accepted version of:

Ammenwerth E, Hackl WO, Hörbst A, Felderer M. Indicators for cooperative, online-based learning and their role in quality management of online learning. In: Boboc M, Koc S (eds.). Student-Centered Virtual Learning Environments in Higher Education. IGI Global. 2018. ISBN 9781522557692. DOI: 10.4018/978-1-5225-5769-2

Indicators for cooperative, online-based learning and their role in quality management of online learning

ABSTRACT

Learning is a constructive and social process that works best in interaction with others. From this perspective, interaction and cooperation are seen as essential for learning especially in online-based learning environments. The objective of this chapter is to propose and test indicators for cooperative online-based learning. The indicators focus on three areas: presence of participants (indicators: access index, access pattern index), participation of participants (reading index, contribution index, completion index), and interaction of participants (answer contribution index, connectivity index, reciprocity index). The indicators can be applied both to students and instructors. The indicators were applied to three online-based courses in higher education. Log data from the learning management system was used. Also, success rates, student evaluations and workload analysis were conducted. Results show that the indicators can be calculated automatically and can provide meaningful information for students' and instructors' dashboards. The presented indicators are tailored to cooperative online-based learning environments, where interaction and cooperation are means of fostering higher levels of learning.

Keywords: Community of Inquiry, Cooperative Learning, Dashboard, E-tivity, Learning Analytics, Social Constructivism, Access Index, Reading Index, Contribution Index, Completion Index, Connectivity Index, Reciprocity Index

INTRODUCTION

Learning is a constructive and social process that works best in interaction with other persons (Vygotzky, 1978). Through interaction and cooperation, students gradually construct systems of shared meanings (Mercer, 1995). Interaction and cooperation are seen as essential for learning in general (John-Steiner & Mahn, 1996), but especially for successful learning in online-based learning environments (Chou, 2002; Dixson, 2010; Lenning & Ebbers, 1999; Zhao, Lei, Yan, Lai, & Tan, 2005). Online teaching should thus be built on a thoughtful instructional design to facilitate interaction and cooperation among students.

Cooperative learning is the instructional use of small groups so that students work together to maximize their own and each other's learning. Different types of cooperative learning can be distinguished, such as formal cooperative learning where students work together to jointly complete specific tasks and assignments; informal cooperative learning where students work together in ad-hoc groups; and cooperative based groups that are long-term, heterogeneous learning groups whose primary responsibilities are to provide support, encouragement, and assistance (Johnson & Johnson, 2013).

To see whether the chosen instructional design is successful in achieving interaction and cooperation, instructors in online-based environments need to carefully monitor students' interaction and cooperation. Monitoring allows them to detect situations where they must adjust their instructional strategy or where they need to support less active or struggling students. To do this, well-defined indicators allowing a quantitative monitoring of interaction and cooperation may be of help to support this task.

Learning analytics is the collection and analysis of data about learning and learning context. The objective of learning analytics is to better understand and improve learning (SoLAR, 2011). With the shift to blended and online learning, and the increasing amount of data available from learning management systems, learning analytics has found its place in education and is increasingly considered as an enabler to transform teaching and learning (Jacqueleen, 2015). In pure face-to-face settings where no learning management system is in place, learning analytics is seldom used as only few data sources (such as information on library use or classroom attendance of a student) are available.

Learning analytics in blended or online-based environments is often based on quantitative indicators of student activity and student engagement collected from learning management systems (Saar, Fors, & Tedre, 2017), such as number of student posts, lengths of posts, continuity of participation, or number of answers (Coll, Engel, & Bustos, 2009; Hrastinski, 2008). These indicators can be easily derived from the learning management system. Yet these indicators may not directly give evidence on the quality of learning (Hrastinski, 2008). Besides quantitative indicators, also qualitative indicators may be used that focus on the content of student posts using content analysis (Chou, 2002; Wen, Yang, & Penstein Rosé, 2014). This is, however, quite time-consuming and cannot be fully automated. This approach is thus not feasible when learning processes must be analyzed in a timely manner. Another approach focuses on describing social interaction patterns of students, for example, in the form of network diagrams (Coll, Engel & Bustos, 2009) and through social network analysis. Typical indicators in this type of analysis are intensity, cohesion, and density of interaction (Saz, Engel, & Coll, 2016; Stepanyan, Mather, & Dalrymple, 2014).

Our approach concentrates on quantitative indicators, as they can be extracted easily and automatically from the log files of the learning management system. This allows a timely feedback to the instructor while the course is still running and also allows immediate feedback to the students. These quantitative indicators could populate student and instructor dashboards, as proposed by the Society for Learning Analytics Research (SoLAR, 2011). Also, these indicators could be an important part of an overall quality management strategy to design high-quality, adaptable online-based learning environments that support instructors in their role as designer (Kalantzis & Cope, 2010).

The objective of this chapter is to propose and test quantitative indicators for cooperative learning in online-based settings. We were especially interested to test the feasibility of deriving indicators from automatically collected log data. We were also interested to see whether the chosen indicators provided meaningful information on student interaction and cooperation and could serve as input for students' or instructors' learning dashboards.

OVERVIEW OF THIS CHAPTER

Research has focused on available indicators from learning management systems and how these can be used to monitor student progress. We chose another way and first propose indicators for online-based learning. We especially focus on indicators for monitoring the interaction and cooperation of students (and instructors) in cooperative online-based learning environments, as we share the perspective of social constructivism and see interaction as essential for learning. These presented indicators comprise, among other things, indicators for the participants' presence, participation, and interaction.

The chapter then presents a case study of three online-based courses where the indicators were applied. We analyze which data is available in the learning management system. We discuss the benefits, but also the limitations and challenges when applying these indicators to online-based learning processes. In particular, benefits and challenges both from the point of view of the instructor as well as from the point of view of the affected students are discussed.

INDICATORS FOR MONITORING INTERACTION AND COOPERATION

The proposed indicators apply and extend the work of Coll et al. (2009), who proposed some basic indicators. This section first justifies each indicator and then summarizes the indicators in Table 1.

As indicators for the **presence of the students** within the course, the following two indicators were defined:

The indicator "access index" is based on the indicator "individual access index" from Coll et al. (2009). This indicator comprises the number of days in which a student is online, in relation to the duration of the course. Coll et al. (2009) define 0.5 as a threshold for this indicator and argue that no participation and interaction is possible below this threshold.

The indicator "access pattern index" is the number of days belonging to a group of at least three days in a row in which a student was absent from the course, in relation to the duration of the course. Coll et al. (2009) defined students as "discontinuous" when they were absent for more than three days at least three times during the course or for at least 15% of the course days in a row. Our indicator was defined based on this idea, but in a way that makes it independent of the course length. Also, to make sure that "100%" is the best value for this indicator, as with the other indicators, this indicator is inverted (i.e. subtracted from 100%). For example, if a student was absent for five days in a row during a course of 20 days (= 25%), the access pattern index would be calculated as 100% - 25% = 75%, indicating that the student had a continuous access of 75% of the course duration.

As indicators for the **participation of the students** in the course, the following three indicators were defined:

The indicator "reading index" was defined as the number of posts that a student has read, in relation to all posts written by other students. Coll et al. (2009) define 0.9 as a threshold for this indicator, which they call "individual reading index". They argue that only a high index indicates joint discussion and construction of knowledge.

The indicator "contribution index" is the number of days in which a student has written at least one post, in relation to all days in which the student was online. The idea is based on the "individual contribution pattern" index of Coll (2009) that is defined as the number of days in which a student posted a contribution, in relation to the duration of the course. Coll et al. (2009) argue that a threshold of 0.6 should be reached for a high level of participation. Our indicator is based only on the number of online days (not on all days) in order to have better information on the activity of the students during their online days and to allow this index to reach "100%" as with the other indicators.

The indicator "completion index" is the number of learning activities in which the student has submitted at least one post, in relation to all learning activities. Coll et al. (2009) define the "individual contribution index" as the number of posts in relation to all required posts. As not all online courses have a fixed required number of posts, the indicator "completion index" merely checks for at least one post per learning activity.

As indicators for the **interaction of the students** in the course, the following three indicators were defined:

The indicator "answer contribution index" is the number of replies that a student has written, in relation to all posts written by this student. Coll et al. (2009) call this indicator "individual answer contribution index". They argue that a certain number of replies is needed so that students can cooperate. They do not give a threshold.

The indicator "connectivity index" is the number of unilateral relationships in a course, in relation to the number of possible unilateral relationships. A unilateral relationship exists if a student has directly replied to another student. For example, in a thread [A → B → C], A and B as well as B and C have a unilateral relationship. The connectivity index relates this to the maximum number of unilateral relationships in a group, which is: number of students − 1 × 2. This indicator is based on the idea of asymmetric relationships (one-way communication) of Coll et al. (2009), who argue that direct answers to posts are an indicator of student interdependency.

The indicator "reciprocity index" is the number of bilateral relationships in a course, in relation to the number of possible bilateral relationships. A bilateral relationship exists if two students have mutual unilateral relationship, that is, that both have directly replied to the other student at least once. For example, given two threads [A → B → C] and [B → A → C], A and B have a bilateral relationship with each other, but both only have a unilateral relationship with C. The reciprocity index relates the number of bilateral relationships to the maximum number of bilateral relationships in a group, which is: number of students − 1. The reciprocity index is by definition smaller than or equal to the connectivity index. The idea of this index is based on the individual reciprocity index of Coll (200).

Summarizing, indicators for presence, participation and interaction were developed. We see presence as a precondition for participation, and participation as a precondition for interaction. Interaction, in turn, reflects cooperation, which we see as a precondition for successful learning.

Table 1 summarizes these proposed indicators for the presence, participation, and interaction of students. All indicators have a minimum of 0 and a maximum of 1 (100%).

Table 1: Indicators for the presence, participation, and interaction of students in cooperative online-based learning, with possible minimum and maximum values.

Indicator	Definition	Possible minimum	Possible maximum
Presence of students			
Access Index	Number of days in which a student was online, in relation to the duration of the course.	0%	100%
Access Pattern Index	Number of days that belong to a group of at least three days in a row in which a student was absent from the course, in relation to the duration of the course; the result is then subtracted from 100%.	0%	100%
Participation of students			
Reading Index	Number of posts that a student has read, in relation to all posts written by other students.	0%	100%
Contribution Index	Number of days in which a student has written at least one post, in relation to all days in which the student was online.	0%	100%
Completion Index	Number of learning activities in which the student has written at least one post, in relation to all learning activities.	0%	100%
Interaction of students			
Answer Contribution Index	Number of replies that a student has written, in relation to all posts written by this student.	0%	100%
Connectivity Index	Number of unilateral relationships in a course, in relation to the number of possible unilateral relationships. A unilateral relationship means that a student has directly replied to another student.	0%	100%
Reciprocity Index	Number of bilateral relationships in a course, in relation to the number of possible bilateral relationships. A bilateral relationship means that two students have a mutual unilateral relationship, that is, both have directly replied to the other student at least once.	0%	100%

APPLICATION OF THE INDICATORS IN A CASE STUDY

We will now present a case study where the indicators were applied to analyze three online-based courses that were held at UMIT, the University for Health Sciences, Medical Informatics and Technology, in Hall in Tirol.

The case study comprises three online-based postgraduate pilot courses with 16 to 21 students each. The courses were pilots for a new online-based master program on health information management that started in 2018. At the time of writing this paper, three pilot courses had taken place, and all of them are included in this case study. Course 1 focused on project management, Course 2 on clinical data warehousing and analytics, and Course 3 on eHealth.

Course 1 lasted four weeks; the other two courses lasted six weeks. The intended weekly workload of the students was 10 to 15 hours. The participants in the courses mostly did not know each other beforehand. The courses were meant to validate a newly designed cooperative online-based instructional design. They were free of charge and open to all interested people with a background in health care. Participants had different professional backgrounds (including nursing professionals, medical informaticians, and quality managers). Participants received a certificate upon successful completion.

The courses were based on a cooperative instructional design where weekly learning activities had to be completed. The design was inspired by a constructivist understanding of learning, with a strong focus on student activation and student interaction. In particular, as instructional frameworks, elements from social constructivism were used by putting a strong emphasis on communication and interaction. Also, elements from situated learning in a community of practice were applied, with a focus on authentic activities and collaborative problem solving (Lave & Wenger, 1991). In addition, the Community of Inquiry framework was used, with a focus on facilitating social presence, teaching presence, and cognitive presence (Anderson, 2008; Garrison, 2007; Vaughan, Cleveland-Innes, & Garrison, 2013). In addition, self-regulation was fostered by asking participants to define personal learning goals at the beginning of the course, by demanding weekly reflections on the individual learning progress, and by organizing regular peer feedback during the course (Kalantzis & Cope, 2010). The overall design was also inspired by andragogy (Knowles, 1984), with a focus on activating preliminary knowledge, on interaction in interdisciplinary teams, and on applying new competencies in the own professional context.

All courses followed the same basic structure. Each course first contained meta-information, including information on learning objectives, content, instructor, and literature. Then, each course consisted of a set of weekly learning activities. Each week, participants had to complete up to seven learning activities. The structure of the learning activities was based on the concept of E-tivities (Salmon, 2013). Based on this concept, each learning activity comprised a description of the intended learning objectives, the tasks to be performed by the participants, and the expected interaction (e.g., discussion of results in a forum). The learning activities were not meant to test competencies, but to allow the students - alone or in interaction with the others - to accomplish the intended learning objectives. Examples for learning activities include: reading literature on a given concept, preparing and presenting a case study, writing a project plan, searching for additional literature, describing a method, contrasting different approaches, criticizing a given approach, conducting a statistical analysis, designing a database. For each learning activity, the necessary materials (presentations, papers, book chapters, or web sites) were provided by the instructor. Each of the three courses had a different instructor.

Moodle was used as learning management system. Participants mostly did not have previous knowledge of the learning management system Moodle that was used in all three courses. Nevertheless, no specific training on Moodle was needed or was offered to the participants.

The entire communication in the pilot modules was asynchronous. Students could work on the learning activities and post or reply to messages at any time they wanted. The instructor was present each day, helped in case of questions and problems, provided tailored input and summaries to the discussions, and gave feedback to the student submissions.

METHODS FOR ANALYSIS OF INDICATORS

Log data from Moodle was extracted in anonymized form and analyzed using the Talend Open Studio software platform (www.talend.com) and Tableau 10.0 (www.tableau.com). This data was used to calculate number of threads, number of posts and the indicators described before (Table 3).

Success rates were calculated based on the number of students who successfully completed all required learning activities. Workload evaluation was based on a daily self-documentation by the students; a web-based documentation form that allowed daily documentation was provided to the students.

At the end of each module, an anonymous student evaluation was conducted that contained both standardized and open questions.

At the end of the course, students also completed the community of inquiry survey (Garrison, Anderson, & Archer, 2000). Results from this evaluation have already been published elsewhere (Ammenwerth & Hackl, 2017) and are not reported here.

RESULTS

Each course resulted in more than one thousand posts by the participants and more than a hundred posts by the instructor, indicating a high level of interaction. Table 2 shows some information on each course.

Table 2: Information on the three online courses

	Course 1	Course 2	Course 3
Participants	16	16	21
Duration	4 weeks	6 weeks	6 weeks
Duration of direct instruction (such as slide presentations or videos)	60 minutes	160 minutes	30 minutes
Number of learning activities	29	25	30
Success rate of participants	9 (out of 16) (59%)	8 (out of 16) (50%)	13 (out of 21) (62%)
Number of discussion threads	362	242	438
Number of student posts (% of all posts)	1,235 (84%)	1,101 (83%)	1,568 (91%)
Mean number of posts per student per week (± standard deviation)	28 (± 11)	19 (± 14)	17 (± 12)
Mean number of posts in one thread (± standard deviation)	4 (± 3)	6 (± 6)	4 (± 5)
Mean number of words in a post (± standard deviation)	72 (± 96)	67 (± 68)	89 (± 108)
Anonymous student evaluation of the course (1 = very good, 5 = very bad)	1.1	1.0	1,2
Student workload	18 ± 6 hours per week	13 ± 3 hours per week	14 ± 2 hours per week

Table 3 presents in detail the results of the indicators related to presence, participation, and interaction for all three courses for the successful participants. The numbers show that successful participants easily reached the threshold as defined by Coll et al. (2009): access index > 0.5 and contribution index > 0.6.

Table 3: Indicators of the three online courses for successful students. A "post" = active contribution to a discussion forum. Numbers indicate minimum | maximum | mean | standard deviation

<table>
<tr><th></th><th>Course 1</th><th>Course 2</th><th>Course 3</th></tr>
<tr><td colspan="4">Presence of students</td></tr>
<tr><td>Access Index
(% of online days)</td><td>0.58 | 0.97 | 0.84 | 0.13</td><td>0.62 | 0.90 | 0.80 | 0.08</td><td>0.57 | 0.96 | 0.75 | 0.11</td></tr>
<tr><td>Access Pattern Index
(% of offline days in a group of at least three days in a row, subtracted from 100%)</td><td>0.76 | 1.00 | 0.89 | 0.09</td><td>0.76 | 1.00 | 0.94 | 0.08</td><td>0.69 | 1.00 | 0.95 | 0.08</td></tr>
<tr><td colspan="4">Participation of students</td></tr>
<tr><td>Reading Index
(% of posts read)</td><td colspan="3">Not applicable, as posts were partly sent automatically by e-mail; no tracking of reading of the posts was then possible in the learning management system.</td></tr>
<tr><td>Contribution Index
(% of online days with at least one own post)</td><td>0.70 | 0.97 | 0.83 | 0.08</td><td>0.55 | 0.97 | 0.76 | 0.15</td><td>0.57 | 0.96 | 0.75 | 0.13</td></tr>
<tr><td>Completion Index
(% of activities with at least one own post)</td><td>0.93 | 1.00 | 0.97 | 0.03</td><td>0.76 | 0.95 | 0.86 | 0.07</td><td>0.69 | 1.00 | 0.84 | 0.10</td></tr>
<tr><td colspan="4">Interaction of students</td></tr>
<tr><td>Answer Contribution Index
(% of replies)</td><td>0.66 | 0.85| 0.75 | 0.06</td><td>0.73 | 0.89 | 0.81 | 0.05</td><td>0.58 | 0.82 | 0.72 | 0.07</td></tr>
<tr><td>Connectivity Index
(% of unilateral relationships)</td><td>1.00 | 1.00 | 1.00 | --</td><td>1.00 | 1.00 | 1.00 | --</td><td>0.69 | 1.00| 0.95 | 0.09</td></tr>
<tr><td>Reciprocity Index
(% of bilateral relationships)</td><td>0.88 | 1.00| 0.97 | 0.05</td><td>0.71 | 1.00 | 0.97 | 0.05</td><td>0.71 | 1.00 | 0.93 | 0.10</td></tr>
</table>

The indicators show that the students were online on over three-quarters of all days (access index). They wrote a post on more than three-quarters of these online days (contribution index). Longer periods of absence of a student were quite rare (access pattern index). Students posted a message for at least 84% of all learning activities (completion activities). Over 70% of posts were replies to other posts (answer contribution index). The connectivity index and reciprocity index are > 0.9, indicating that most students directly replied to all other students at least once.

The indicators were then also applied to the instructor to analyze the presence, participation, and interaction of the instructor. A new indicator was added for this purpose, called "teacher presence index", which was defined by the number of posts written by the instructor, in relation to all posts written in the course. Results are presented in Table 4.

Table 4: Indicators for the instructor of the three online courses. A "post" = active contribution to a discussion forum

	Course 1	Course 2	Course 3
Presence of instructor			
Access Index (% of online days)	0.91	1.0	0.74
Teacher Presence Index (% of own posts)	0.16	0.17	0.09
Participation of instructor			
Reading Index (% of posts read)	*Not applicable, as posts were partly sent automatically by e-mail; no tracking of reading of posts was then possible in the learning management system.*		
Contribution Index (% of online days with at least one own post)	0.93	0.69	0.77
Interaction of instructor			
Answer Contribution Index (% of replies)	0.79	0.82	0.79
Connectivity Index (% of unilateral relationships)	1.0	1.0	1.0
Reciprocity Index (% of bilateral relationships)	1.0	1.0	1.0

The indicators show that the instructors were online on over three-quarters of all days (access index). They wrote a post on at least 70% of these online days (contribution index). Overall, up to 16% of all posts were posted by the instructor (teaching presence index).

DISCUSSION

Data relating to the learning process of the students in online courses nowadays is easily available through the learning management systems, but exploitation of this data outside controlled settings still seems to be rare. Indicators are rarely used to optimize learning processes (Li, Bao, & Xu, 2017). It is expected, however, that learning analytics will be widely used in online-based education in the next few years (Avella, Kebritchi, Nunn, & Kanai, 2016).

This chapter proposed indicators for the presence, participation, and interaction of both students and instructors and applied them in three online courses. The results show that these indicators can be calculated based on the available log data from the learning management system that was used, in this case, Moodle. The indicators for the three courses were quite comparable, which is not surprising, as all courses followed the same cooperative instructional design.

Moore (1989) distinguishes learner-content, learner-instructor, and learner-learner interaction as basic types of interactions (Moore, 1989). Our indicators focus mostly on learner-learner and learner-instructor interaction, as studies show that the interaction and cooperation of students with others and especially the participation in online discussions have a positive impact on the learning process and learning outcome (Cho, Gay, Davidson, & Ingraffea, 2007; Palmer, Holt, & Bray, 2008). However, indicators to analyze learner-content interaction could be easily added (e.g., proportion of course materials that is read).

Learning analytics indicators and the instructor

How can an instructor make use of these indicators? At least two scenarios can be distinguished. The first scenario is using the indicators "on the fly". This means monitoring the indicators while the course is running (Davies, Nyland, Bodily, Chapman, Jones, & Young, 2017). The second scenario is using the indicators to perform a post-hoc analysis of the course after it is finished.

For the first scenario, the indicators provide the instructor with important information on the engagement of the students. The instructor can see, for example, when students are absent from the course for a longer period of time and can contact them to offer support. The instructor can also identify a decreasing trend in access rates of individual students or of the group as a whole and intervene accordingly. The instructor can also see students who are online, but who do not participate actively. Especially at the beginning of an online course, the instructor could then contact these students and motivate them to start to contribute. Also, the instructor can monitor the level of interaction of the group. All this information can help to track the activities of students during the course and may help to identify those who need some support. Thus, in this scenario, indicators are used to monitor and support learning processes (Coll et al., 2009).

Studies in educational data mining have shown that it is also possible to predict students' retention and students' performance based on a set of indicators, student participation and student interaction being among these indicators (Papamitsiou & Economides, 2014; Yu & Jo, 2014). The instructor could thus especially focus on students who show a high probability of failure and intervene early enough in the course to help the student get back on track.

For the second scenario, after the end of the course, the instructor can review the indicators for the whole course and see whether intended levels of presence, participation, and interaction have been reached both for individual students and for the whole group. The instructor can also check whether the indicators increased or decreased over the duration of the course and how this was influenced by interventions of the instructor. In this scenario, indicators are used to optimize the instructional design for the next course (Li et al., 2017).

For both scenarios, an instructor dashboard or educator dashboard (SoLAR, 2011) is helpful where the indicators are displayed both regarding each individual student as well as for the whole group. The idea of dashboards is discussed further below. In these dashboards, besides the proposed indicators, further data could be added, such as student demographics, assessment results, final grades, or self-assessments of skills or emotional states.

These two scenarios can be extended by a third scenario, where the program management has a program dashboard to scan relevant indicators of all courses within a given curriculum. This could provide information on student activity, learning outcome, and learning evaluation of all courses within a program and so help to identify weak points (such as courses with low access rates and low student evaluations) and to improve the overall curriculum (Avella et al., 2016).

Learning analytics indicators and the student

Indicators can also be used to inform the students on their learning process. Indicators can give students personalized feedback on their learning progress and help them to optimize their learning strategies (Li et al., 2017; SoLAR, 2011). Studies indicate that this support can improve self-reflection (Papamitsiou & Economides, 2014) and increase learning outcome (Kim, Jo, & Park, 2016).

When discussing the use of instructor and student dashboards, however, institutions need to take into account that learning analytics touches on important ethical and legal issues. For example, it needs to be clarified whether students have to explicitly consent to data collection and data analysis or not, whether instructors should only see anonymized or aggregated indicators (and not indicators related to an individual student), or whether all prediction algorithms that are used should be made available to all instructors and students involved (Sclater, 2015).

There seem to be tensions in several areas: tension between the students' wish for personalized feedback from the system and the demand that this feedback is not visible to the instructor; between the students' wish for an opt-out option and the need to provide equal information and equal opportunity for feedback to all students; and between the wish for personalized feedback and the fear of losing students' autonomy and self-regulation (Roberts, Howell, Seaman, & Gibson, 2016).

Thus, while a recent U.K. survey indicates that 91% of students would be happy for their lecturers to track their progress week by week if it helped them to achieve better grades, and that 76% believe better use of learning analytics could be the key to improving retention rates (Kortext, 2016), the use of learning analytics has to be carefully discussed at the university level before it is implemented on a broader scale.

Student and instructor dashboard

As discussed before, student and instructor dashboards make it possible to present tailored learning analytics indicators to help monitor and support learning processes, foster self-reflection, predict learning outcome, and improve instructional design. Still, long-term evaluations of the impact of dashboards on efficiency and effectiveness of learning are limited and inconclusive (Verbert, Govaerts, Duval, Santos, van Assche, Parra, & Klerkx, 2014).

Verbert et al. (2014) provide several examples of what these dashboards could look like. They note that the usefulness of these dashboards depends to a large extent on automated tracking of all, or at least a major part, of learning activities. Dashboards therefore seem mostly suited in fully online-based learning environments where automatic tracking of all learning activities is much easier to be obtained compared to face-to-face or blended-learning settings.

In any case, the needs of both students and instructors are different and need to be explored separately. Dashboards must be designed with regard to the specific needs of these groups. Especially the students' wishes need to be considered, and students should be involved in the development of dashboards (Roberts et al., 2016; Verbert et al., 2014).

Limitations of the indicators

There are some limitations of the presented indicators. First, connectivity index and reciprocity index only consider direct replies, not replies that are responses to a much earlier post. Thus, more detailed content analysis would be needed, which can, however, not be automated easily.

Second, while these indicators help to quantify student presence, participation, and interaction, they do not present information on learning outcome. While it seems intuitive to take the activity of students as indicator for the quality of learning (Mazzolini & Maddison, 2003), the causal relationship cannot be assumed in all cases. To assess the quality of learning, additional indicators need to be added, such as students' grades or students' self-assessments on learning outcome. Also, indicators from social network analysis, such as density (Saz et al., 2016), or indicators for social presence, cognitive presence, and teaching presence as proposed by the community of inquiry (Arbaugh, Clevland-Innes, Diaz, Garrison, Ice, Richardson, & Swan, 2000) could be added.

Third, the absolute values of the indicators obviously depend strongly on the chosen instructional design (e.g., the amount of expected interaction between students). Thus, courses can only be compared when they follow a comparable instructional design. Indicators alone, without context information, thus do not allow benchmarking and comparison of courses, for example, on a program level.

Fourth, we did not yet investigate whether certain indicators are more important than others, how each indicator contributes to successful learning, and which instructional design strategies may have an influence on which indicator. This must be done in future studies.

The indicators do not comprise the "total login time" in the learning management system, as proposed by some authors such as (Yu & Jo, 2014), as important learning can occur outside the login time (such as reading a book before logging in and joining the online discussions).

CONCLUSION

This chapter presented and piloted some learning analytics indicators on the presence, performance, and interaction of both students and instructors. These indicators can be derived automatically from learning management systems and could be visualized via student and instructor dashboards. These indicators are tailored to cooperative online-based learning environments, where interaction and cooperation are fostering higher levels of learning (Gunawardena, Lowe, & Anderson, 1997). They are an expression of a participatory learning culture (Jenkins, 2009).

In our three courses, we found that students were satisfied with the chosen instructional design, as the student evaluations show. The instructional design fostered an activating and cooperative way of learning, as the learning indicators show. In particular, we saw the high number of posts per student, the high contribution index as well as the high connectivity and reciprocity index as clear indication of close cooperation and a successful community of inquiry. This finding is supported by the results of the community of inquiry survey. In the free-text answers to the student evaluation, students especially stressed the benefits of cooperative working based on authentic learning activities. As a limitation, the presented way of teaching and learning is quite time-intensive for both students and instructors, as the student workload evaluation shows.

The indicators, together with other indicators on learning outcome, can support learning analytics with the aim to "(a) classify students into groups according to their performance, (b) identify students who are likely to fail (and work on assistance plans), (c) be able to predict the future performance of students, (d) identify excellent performance traits and how these impact excellent learning outcomes, (e) identify tasks that estimate high performance and significant, effective engagement, and (f) improve teachers' performance" (AlShammari, Aldhafiri, & Al-Shammari, 2013).

As a next step, we plan to continue the collection and analysis of the presented indicators, together with the community of inquiry survey, in all further online-based modules. The aim is to identify those indicators that are the best predictors for building a community of inquiry and for student success in an online course. We will then verify whether this information, as part of an instructor dashboard, indeed helps us to identify and support students who show an increased risk for failure.

ACKNOWLEDGMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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KEY TERMS AND DEFINITIONS

Community of inquiry: group of individuals who collaboratively engage in purposeful critical discourse and reflection to construct personal meaning and confirm mutual understanding.

Cooperative learning: educational approach aiming at organizing learning activities into academic and social learning experiences by promoting interaction and communication.

Dashboard: application that visualizes various indicators for learning processes and learning outcomes either for the student or for the instructor.

E-tivity: asynchronous activity where learners interact with one another and with the instructor in an online communication environment in order to complete a particular task.

Indicator: measurable variable used as a representation of an associated factor or quantity.

Learning analytics: the collection and analysis of data about learning and learning context.

Online-based learning: learning mediated by online-based applications.

Reciprocity: bilateral interaction of two learners in an online-based learning setting.

Social constructivism: a theory of knowledge according to which learning is socially situated and knowledge is constructed through interaction with others.