Students Expectations on Learning Analytics: Learning Platform Features Supporting Self-regulated Learning

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Abstract: The article presents results of a survey and interviews mapping students' expectations and needs on learning analytics. The discussion focuses on the functionalities and features which were considered to support self-regulated learning in Moodle learning environment. The aim of the discussion is to identify how the reported student needs could be met by utilizing descriptive, prescriptive or predictive learning analytics.
It was discovered that students need and expect certain functions in the digital learning environment to support self-regulated learning. The survey results indicate that students mainly demand for tools which could help them in planning and scheduling their studies. Secondly, to be able to monitor and regulate their performance, they need progression tracking tools as well as timely and constructive feedback. Features of descriptive analytics were considered the most useful for self-regulation, while the expected benefits of prescriptive and predictive analytics were more controversial and tentative.

1 INTRODUCTION

Learning analytics is a relatively young field of research, and its use in the field of education is still in its infancy. Learning analytics is a sub-genre of data analytics and does not have a definition set in stone. Learning analytics is broadly defined as the collection, measurement and analysis of data produced by a learner in a digital learning environment. The data processing aims at understanding and optimizing learning and its contexts (Society for Learning Analytics Research, 2020).

Although the data in digital learning platforms is provided by the students, their perspective has mainly been bypassed in the development of learning analytics tools (Hooli, 2020; Buckinham, Shum, Ferguson, Martinez-Maldonado, 2019). Therefore, learning analytics tools often only measure and record actions which present useful information to the teacher, but not necessarily to the students (Hooli, 2020). Moreover, even if students could benefit from the data collected in the online learning environment, they may not have access to view it. In recent years, most digital learning platform providers have started to develop learning analytics tools which are available to students, ie. they are able to themselves monitor and utilize the data accumulated from their online studies.

The tools for collecting, analyzing, and interpreting learning data will not develop unless learning analytics is researched and advanced in a user-driven way. If the tools are found to be unnecessary or useless, they will not be deployed. Silvola, Jylkäs and Muukkonen have concluded that in order to develop analytics tools that students want to use, the tools should meet the information and support needs of students in their daily lives (Silvola, Jylkäs & Muukkonen, 2020). Therefore, it is important to map the real need of end-users of learning environments – both teachers and students – and to critically assess if the data collected really benefits them.

This article is based on a survey and interviews conducted between November 2020 and February 2021 in the MOPPA project (Motivation och självreglering på inlärningsplatta med hjälp av inlärningsanalytik). The aim of the survey and interviews was to map students' experiences of digital learning environments, identify everyday support needs for online learning and find out which activities, tools and pedagogical elements contributing to the collection of learning data in digital learning platforms are considered to increase students' self-regulation and motivation.

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On the basis of the survey some key needs were found in the context of Moodle learning environment used in Haaga-Helia University of Applied Sciences. This article specifically discusses the tools, activities and functionalities which the respondents of the survey found useful and supportive of their learning process. The reported solutions (either pedagogical or technical) which were believed to facilitate learning, are viewed as either existing or possible data collection points for descriptive, prescriptive or predictive learning analytics. Practical suggestions concerning the development of learning analytics tools are made on the basis of the findings.

2 DATA ANALYTICS IN DIGITAL LEARNING ENIVRONMENTS

Learning analytics is commonly divided into three types: descriptive or diagnostic, prescriptive and predictive analysis. Gröhn and Nevalainen have made a comparative analysis of various online learning platforms with respect to the in-built learning analytics tools available. They report that the analytics tools in the platforms included in their analysis mainly offer descriptive or diagnostic learning analytics. There are yet only a few tools or options for using predictive analytics available, and there's a lot of variation in the use of prescriptive analytics (Gröhn & Nevalainen, 2018). Even though tools and models for predictive analytics such as identifying likely drop-outs have been developed, they have not been widely adopted in higher education (Viberg et el., 2018). Gröhn and Nevalainen conlude that learning analytics in the platforms scrutinized in their report shortly means monitoring the various learning actions, collecting the course resources and assignments into a comprehensive view and providing reminders or notifications on the deadlines and materials to be studied. To summarize, the data offered to learners includes their progression on a general level, on a specific course and with the chosen assignments. Most analytics tools also offer separate views for submitted assignments and those yet to be done (Gröhn & Nevalainen, 2018).

2.1 Previous Studies of Students' Expectations on Learning Analytics

Schumacher and Ifenthaler have mapped students' expectations on learning analytics within the framework of the three phases of self-regulation as outlined by Barry Zimmerman (2002): the forethought phase, the performance phase and the self-reflection phase. In this framework self-regulation is understood as a set of metacognitive and cognitive processes initiated and maintained by the students, to carry out the tasks given in any context of learning (Zimmerman, 2002). The students' expectations on learning analytics in the study of Schumacher and Ifenthaler were recognized as to-do lists, reminders of deadlines, tools for planning, clear learning goals, motivational aspects and individual recommendations (forethought phase); monitoring competence level and development of skills, additional or personalized material and assignments, recognition of offline and social learning (performance phase); and self-reflective assignments and feedback (self-reflective phase) (Schumacher & Ifenthaler, 2018).

Students' expectations towards learning analytics have been studied in Finland previously in the APOA project. In the workshops organized for students, the following ten themes emerged on which learning analytics is expected to offer support: 1) Defining and monitoring learning objectives, 2) Monitoring learning activities, 3) Monitoring and visualizing the learning process, 4) Interaction, 5) Feedback, 6) Competence development assessment, 7) Provision of study material, 8) Influencing the process or the content of the course, 9) Improving teachers' technical competence and 10) Time management and study skills (Hartikainen & Teräs, 2020).

2.2 Moodle

In the Moodle learning environment used in Haaga-Helia, the analytics tools available to the student are mostly descriptive. These descriptive tools include Completion Progress block, which collects and visualizes information about the completion of scheduled tasks as well as activities and resources in any course area. The function is not automatic; the teacher activates it if desired and makes it available to students. Tools for collecting and organizing learning data also include the Gradebook and especially the personal Dashboard which is a kind of landing page and summary view that the student can customize and from which they can see the general situation of all their courses (including completion percentages of each course, if progress completion is enabled). The dashboard includes a link to the site-level calendar tool which collects deadlines from all the active courses available to the student. Students can add various blocks into their dashboard, such as timeline, upcoming events, progress tracker, and latest announcements. The blocks collect data from all the course areas in which the student participates.

The range of tools available to the teacher is wider and there are e.g. log data, reports, and activity-specific usage statistics that students do not have access to. All Moodle activities (e.g. forums, test, assignment, lesson, etc.) collect information about the student's activity, such as the amount of views. This information is only visible to the teacher, while the student can only access the material he or she produces (i.e., assignment submissions, test attempts, own files, forum posts, and comments). This information, however, is scattered and not presented as a single comprehensive course-level view or dashboard to student.

Possibilities for prescriptive analytics in Haaga-Helia's Moodle are limited. The test activity enables automated feedback and giving instructions to the student based on the question or test results. There are also automated reminders used for activating students to submit their assignments before deadlines. Teachers may use reports to sort out inactive students on particular activities and send messages with further instructions, but all this has to be done manually. Finally, neither teachers nor students have any tools available for predictive analytics. The Moodle Learning Analytics API is installed in Haaga-Helia's Moodle, but all the default learning analytics models are disabled.

3 METHODOLOGY

As one of the purposes of the project was to identify and explore the connection between student self-regulation and learning analytics, the framework for the survey was based on Zimmerman's model of self-regulated learning. It was also used by Schumacher and Ifenthaler in their study of students' expectations on learning analytics as reported earlier.

3.1 The Survey

The survey consisted of 25 questions divided into three question sets. The first seven questions regarded background info, and the next seven questions mapped the students' preferences concerning online learning. The final set of 14 questions included structured questions on the students' perception of their self-efficacy level and their experiences on certain pedagogical solutions and functionalities available in their online courses. There were also open-ended questions about the perceived barriers to online learning, the expectations and needs for tools or actions supporting learning, and two questions on motivational issues. This article focuses on the responses given in the open-ended questions; however, the issue of motivation was omitted from this discussion.

The open-ended questions of the survey were analysed through qualitative content analysis. The needs (functionalities or tools) reported by the respondents were first categorized according to their main theme, identifying repeating key words and phrases. Thematic analysis also utilized semantic analysis. Furthermore, the identified main themes were recognised as needs towards either descriptive, prescriptive or predictive analytics.

The survey was sent to selected student groups in blended learning study programs, but participation was voluntary and the answers were handled anonymously. There were 47 responses and most of the respondents were students of business and entrepreneurship or IT and digital services. The mean age of the respondents was 34; the youngest was 21 and the oldest 56. They were mostly adult students with a previous degree or work experience.

3.2 The Interviews

The survey was followed by voluntary semi-structured interviews with seven students who had also participated in the survey. The interviews included four open-ended question and two semi-structured question based on the survey results. With the semi-structured questions, the interviewees were shown a table that summarized the tools or actions supporting learning as identified in the survey responses, divided into the three analytics types. The summary was made on the basis of the survey responses, and it included the most often suggested features and functionalities. However, some options were added simply because it was presumed that most students were not fully aware of the possibilities of learning analytics in learning platforms. Table 1 shows the categories including the titles they were presented with. The first column represented needs for descriptive analytics, the second column represented needs for prescriptive analytics and the third column consisted of needs for predictive analytics.

The students were asked to choose which of the categories included features that best support self-regulated learning and motivation in general. They were also asked to highlight any three features which they personally considered the most useful for them.

The interviews were conducted by the author and another researcher and they were transcribed. All seven interviewees chose to have a Zoom or Teams interview. Oral informed consent to record the

Table 1: The division of actions and features supporting self-regulated learning on the learning platform, categorized under the types of learning analytics.

Monitoring of learning and performance	Tutoring the study process in the learning platform	Course level predictions
• The learning platform informs you what is done/undone • All assignment deadlines clearly visible • Notifications on assignments • Automated retrieval of the material/course content were you left off • Information on the time you have spent browsing through the course data and material • You may check the assignments /materials in which your learning has slowed down or in which some challenges are identified. • Your progression as compared to other students • Your competence development as compared to the expected learning outcomes of the course	• Personalized reminders or suggestions • A certain study path or method of progression is suggested for you • Certain course contents and resources are selected and offered to you (based on your self-assessment or your written tasks) • You are given tips and instructions based on learning results and assessments.	• The reading time of course material is estimated (based on your previous reading tasks) • Time for course completion is estimated • The course grade is estimated (based on the completed assignment grades and/or your efforts in the course) • Prediction on the risk of dropping out of the course

session was gained in the beginning of the interview by all interviewees. The interviews lasted between 15 and 28 minutes. The questions were aimed at revealing in more detail the reported needs, experiences and perceptions of the students within the context of learning analytics. The purpose of the interviews was not to gain any new information but rather to find further explanations for the identified needs and to elaborate on the specific themes that emerged in the survey. The interviews complemented the thematic analysis of the survey responses.

4 RESULTS

In an open-ended question of the survey, students were asked to write about anything they feel could help them (self-regulate) in their study process in online learning. Respondents were especially encouraged to think if they had any needs for a specific feature or functionality in the learning platform. Eleven students did not have any suggestions nor reported specific needs; in addition, there were some replies focusing on pedagogical issues. However, two major themes emerged: a demand for time management and progression tracking, and the need for feedback.

4.1 Time Management, Progression Tracking and Study Planning

In 22 responses, a need for scheduling and planning tools was highlighted, with a strong emphasis on the follow-up of deadlines:

"A to-do list in one place would be great. I could add notes myself about submitted assignments and schedule all undone assignments."

Another feature or functionality considered important was a comprehensive dashboard view for monitoring all the active courses at one glance:

"A comprehensive view of all active courses, currently I'm building such a view with excel myself. The view includes all contact sessions (online/ classroom), personal events, deadlines and my own scheduling of which course assignments I am working on and when."

"[A tool] that shows me instantaneously which courses are ongoing and what happens in them and how I have progressed and what are for instance the assignment deadlines, and all of these in one location."

The majority of student needs were connected with progression monitoring. This was needed both on a single course level and within the framework of the entire study program:

"It would be nice to see information of my actions and time usage, and a comprehensive view of my progression in a particular course and within my studies as a whole. Now this information is scattered in different locations and in a majority of the courses, the progression tracking does not work correctly."

Some students specifically emphasized the importance of visualizations such as heat maps, visual timelines and progress bars. One of the respondents even claimed that learning platforms should be more like project management systems where students would be able to manage all learning tasks according to their own schedule. This sort of Kanban-style view on learning emerged in the responses quite often and it was evident that tools for time management are certainly needed. However, it is interesting that the responses had a task-oriented edge as they did not reflect the need for monitoring competence development, as was found in the student workshops of the APOA project and in the study by Schumacher and Ifenthaler. According to Zimmerman, setting personal goals in the forethought phase of self-regulated learning, and monitoring one's performance in respect to the expected learning outcomes in the monitoring phase are functions supporting self-regulation (Zimmerman, 2002). Nevertheless, this was not highlighted in the students' needs in this survey. Since the need for keeping track of deadlines and assignment submissions was emphasized, it appears that instead of having problems with achieving the expected learning goals, the metacognitive difficulties were a bigger issue. Apparently, some students struggle finding suitable strategies for online learning and they may have some problems with self-regulation, but only in terms of time management. This is where they expect help form learning analytics.

4.2 Different Types of Feedback

The next important viewpoint after time management was the question of feedback. 15 students reported issues especially with communication and feedback, and it was evident that tools were needed for a more effective and timely communication concerning the students' overall status, course and task level progression and the level of engagement:

"My work progresses/does not progress would be a good button to have in all courses, this is how teachers would know more about the student and they could give instructions and push students forward in doing the assignments."

Such a feature might help teachers in identifying students who are at greater risk of dropping out or who may have trouble with their cognitive or metacognitive processes (i.e. self-regulation). This sort of need for a process-oriented feedback was, however, in the minority. The responses emphasized more of outcome-oriented feedback, which is what most learning analytics dashboards usually support (Sedrakyan, Malmberg, Verbert, Järvelä & Kirschner, 2018). Sedrakyan and colleagues point out that providing relevant type of feedback in learning platforms depends on identifying the factors behind students' (low) performance; any learning analytics dashboard should be able to differentiate whether the student has cognitive problems (difficulties in understanding the tasks) or behavioural problems (difficulties in motivation or putting enough effort into studying) and offer feedback for the purposes of cognitive development or behavioural changes (Sedrakyan et al., 2018).

In the survey, most of the respondents hoped for instant feedback or at least feedback given relatively promptly after the assignment submission:

"Feedback is needed in every course soon after an assignment is submitted in order to be able to learn. In this course feedback was delivered quickly, but this not always the case."

"In math course there were assignments which had instant feedback on whether or not the answer was correct. I wish there were more of this sort of gamified assignments."

Well-timed feedback does not only help students to self-regulate their learning efforts, but it also helps students in identifying their competence level and ultimately it leads to better learning results. For example, in a study with 500 students carried out by Liu and Cavanaugh, the teachers' constructive and timely feedback comments had significant effect on the students' final scores in a math course (Liu & Cavanaugh, 2012).

It is worth considering a learning analytics functionality which could sort out students who would benefit the most from feedback without any delay, since many of the responses expressed dissatisfaction with the timing of the feedback.

"The weekly assignments should be checked and feedback should be received earlier than the end of the course. Often course material is based on the previous weeks' assignments and if I have understood something wrong or have no competence in the beginning of the course, there is no way to fix it in the end."

Sedrakyan and colleagues have suggested, based on their research on learning analytics dashboards as a source of feedback, that the optimal time for feedback can be determined by detecting any anomalies or challenges in the learning process (Sedrakyan et al, 2018). One survey participant suggested that in connection with the assignment submissions, there could be an optional button for asking feedback (especially in tasks were feedback is usually not given). This could benefit students who need more guidance while teachers are able to reduce their work load by not giving feedback to everyone on all tasks. It has been discussed that as students differ in their readiness for self-regulatory learning, support should be offered to the students with weaker metacognitive skills (Nussbaumer et al., 2015). Regulating the level and receive time of feedback according to the learner's needs is what learning analytics dashboards could be used for, as Sedrakyan and colleagues have also proposed earlier (Sedrakyan et al, 2018).

4.3 Behavioural or Cognitive Feedback?

Earlier studies have outlined the types of cognitive feedback into corrective, epistemic and suggestive feedback (Alvarez, Espasa, Guasch, 2012; Guasch, Espasa, Alvarez & Kirschner, 2013). Corrective feedback points out false conclusions, solutions and decisions; epistemic feedback provides analysis for critical reflection and suggestive feedback gives advice to the learner on how to proceed and what to improve. All feedback types may play a role in supporting self-regulated learning, but from the point of view of learning analytics, corrective and epistemic feedback types are more descriptive and suggestive feedback contributes to prescriptive analytics. Automated feedback in learning platforms can form a basis for prescriptive analytics for the students – at least if the feedback is accompanied with suggestions or instructions on what to do next on the basis of the results.

Many of the survey responses regarded feedback as more of a verification of the task being completed successfully, and it can be concluded that feedback is an integral feature of descriptive learning analytics. Receiving correct answers is considered important, as is the descriptive assessment of what went well and what went wrong, as one student responded. The need for instant, corrective feedback was evident, but it remained a bit unclear whether this type of feedback was considered cognitive or rather more behavioural. Therefore, feedback was chosen as one of the key topics in the interviews and the interviewees were asked to describe their notion of good feedback in more detail. They were also asked to define if the source of feedback (teacher, peers or learning platform (automated or auto-generated feedback)) had any significance to them.

The responses were quite univocal: good feedback is well timed, constructive (cognitive) and supportive. The first two characteristics were equally important but the difference between behavioural and cognitive feedback clearly emerged. Behavioural feedback should be instantaneous, as one interviewee described:

"In fact it is not really feedback, it is connected to what came up previously, that when I registrate on a course, I don't actually know if I was accepted or not. […] That gives no confirmation or such. […] For myself, I prefer receiving the feedback in this situation directly from the system. Like "great job, this is now completed, it is done". (Interviewee 1, female)

There were three other interviewees who brought up similar viewpoints describing instant, automated feedback:

"It can be continuous feedback, like whenever you submit an assignment, you would get "Great, xx % of the course is now completed". It may be generic, but it still leaves a good feeling." (Interviewee 5, female)

Many of the interviewees distinguished the automated feedback in the platform as being more behavioural and the (delayed) manual feedback given by the teacher as more cognitive and important:

"The correctiveness is probably the priority, in a sense that if it comes afterwards, at least you know for the future what went wrong even if the feedback did not help you in the learning process during the course". (Interviewee 4, female)

The responses imply, as has been concluded in earlier research, that behavioural feedback is just as important as cognitive feedback because it provides students opportunities to reflect on the learning process, thus helping students self-regulate their learning (namely, monitoring, planning and adapting) (Sedrakyan et al., 2018).

Cognitive feedback is a bit more flexible in terms of perfect timing, but nevertheless the time between assignment submission and receiving feedback should not be too long as it has a negative effect on self-regulation, especially if actions are expected on the basis of the feedback. An interviewee described the mismatch between personal schedules, deadlines and received feedback, which led her to drop out of the course:

"I got constructive feedback of which I realized that I have to a lot to correct, but right now I am really busy at work and I have no time to make the corrections. […] It was like, the (final) deadline in this assignment had to be set by myself and I had set it for the day after tomorrow. I got the feedback a week earlier, so I just don't have the time [to make the corrections]. If there had been a possibility to postpone the deadline, then of course.” (Interviewee 7, female).

The perfect timing of the feedback thus seems to depend on the quality and content of the feedback. Another student suggested that the date when feedback is available should be announced in the learning platform, to be able to plan the study process in the course to match with the schedules of personal life. Such a feature is probably quite easy to add in the settings of the activity tools in online platforms, and it could contribute to the data being collected into learning dashboards for progress monitoring.

The type and purpose of the feedback also affects the preferences on the feedback source. Cognitive feedback is expected from the teacher on specific assignments and overall competence development. Some suspected that artificial intelligence could not offer as good feedback as a teacher. The reason was that the teacher was considered an expert, and the view of an expert was highly appreciated. Similarly, if feedback is merely behavioural and confirmative by nature, it can be automated or auto-generated by the learning platform:

“I don’t think there is a problem with whether the feedback comes from the machine or the teacher. It depends on the quality of the feedback, of course. It is not certain that you’ll get more than “ok” from other students or the teacher. So if it [feedback] comes from the computer or the teacher, it doesn’t matter.” (Interviewee 6, male)

“It depends on the type of feedback. If you only do a test in which you choose alternatives, it is ok to get the feedback from the system. No further comments are needed. But if the assignment is a written essay with reference material, it is nice to get written feedback, not just a numeral grade.” (Interviewee 3, female)

Nearly all interviewees claimed that it is good to have multiple sources of feedback. Interestingly enough, supportiveness was expected mostly from peer feedback. Peer feedback was also considered as part of the learning process or as a task for practicing cognitive skills such as argumentation:

“A few courses have had peer review practices and with fellow students, they don’t necessarily have the skills to give feedback. It should be trained more before practicing it.” (Interviewee 6, male)

Therefore, constructive feedback was not really expected from peers. The benefits of getting positive confirmations and different viewpoints were, however, acknowledged. Peer feedback was suggested to be incorporated in the learning platform with simple and easy ways, such as giving star ratings or thumb-ups. Students preferred fast and effortless ways of giving peer feedback, since group and individual assignments were considered arduous and time-consuming.

The importance of peer evaluation lies within co-regulated learning as students learn to regulate their efforts when they are being compared to others’ behaviour and outcomes (Sedrakyan et al. 2018). However, in the survey, only 15% of the respondents thought it would be useful to have a comparative report of their progression and competence development with respect to their peers. 60 % replied that such a view would not benefit them and 25 % were not sure if such a function was useful. The issue was discussed by some of the interviewees; one student felt peer comparison dashboards might work because of the competitive element, but another student regarded it as possibly disturbing from the point of view of self-regulation.

4.4 Descriptive Analytics: A Must Have

When shown the table 1 during interviews, all of the students selected descriptive analytics as the most important and useful category from them. One student even claimed that descriptive analytics is a norm and should be available by default, so it should not be a matter of choice or preference. Another student chose descriptive analytics as the most important in the context of independent online studies, but claimed that in blended learning course, prescriptive analytics is needed more. However, this overall opinion does not fully match with the features which the students selected as their favourites. The summary of their choices is described in table 2; the number of students who selected the item is shown in brackets.

There were two choices made outside the presented table: the other one was an access point for all material on a single course and the other was a view based on received feedback (how well the student had succeeded as compared to the assignment requirements). These two choices may, however, be categorized into features of descriptive analytics.

To be able to view and monitor what is done or undone was the most important feature, as the survey responses also revealed. Currently, in Haaga-Helia’s Moodle such as view is offered on a course level (the course gradebook and on some courses the progression tracking block). Within the context of the whole study program, monitoring of one’s progression is not available in Moodle and that was one of the issues criticized by the students. They feel it is not easy to log into another system – or at worst into multiple systems – to get a comprehensive view of their studies. This sort of overall view could be constructed with Moodle’s Learning Plan tool,

Table 2: The division of actions and features supporting self-regulated learning on the learning platform, the amounts of student selections in brackets.

Monitoring of learning and performance	Tutoring the study process in the learning platform	Course level predictions
• The learning platform informs you what is done/undone (5) • All assignment deadlines clearly visible (2) • Notifications on assignments (2) • Automated retrieval of the material/course content were you left off (0) • Information on the time you have spent browsing through the course data and material (1) • You may check the assignments /materials in which your learning has slowed down or in which some challenges are identified. (1) • Your progression as compared to other students (0) • Your competence development as compared to the expected learning outcomes of the course (1)	• Personalized reminders or suggestions (1) • A certain study path or method of progression is suggested for you (4) • Certain course contents and resources are selected and offered to you (based on your self-assessment or your written tasks) (0) • You are given tips and instructions based on learning results and assessments. (0)	• The reading time of course material is estimated (based on your previous reading tasks) (0) • Time for course completion is estimated (0) • The course grade is estimated (based on the completed assignment grades and/or your efforts in the course) (2) • Prediction on the risk of dropping out of the course (0)

complemented by the Competency tool. Or alternatively, a plugin or an integrated external software could be used for offering a comprehensive student dashboard for study progress monitoring on a study program level. On a course level, the current tools for tracking progression seemed to be enough, but students hoped the tools would be used regularly and consistently in all study units.

Other preferred features of the listed descriptive analytics were the assignment notifications and view of upcoming (and past) deadlines. The responses do not clearly indicate if the Moodle calendar in student dashboard is in efficient use; but at least it is possible to use the calendar as a tool for planning and gathering all the deadlines from all courses in one location. Students may also mark their own events in the calendar.

Descriptive analytics and the need for it was widely discussed and explained by the students in the interviews. For example, the possibility of monitoring one's time usage was an interesting option for most; clearly it was considered as a potential way of regulating the personal study process and efforts:

"I like to analyse how I've spent my time. Information on what I've used my time for in the course and how long I've spent moving around in the environment could help me in defining if I have used my time reasonably." (Interviewee 7, female)

"Sure, it would be interesting to see how long I've used for a particular task. In my everyday life there is quite a many interruption." (Interviewee 6, male)

Another student was more suspicious of the ability of learning analytics to provide accurate study time data, simply because she regularly used to download the course material and read it offline. Furthermore, being able to identify challenging tasks or materials was considered useful in principle, but the students suspected that in practice it would be difficult to define reliable indicators. As one of the students remarked, used time and the amounts of clicks do not necessarily correlate with challenges or difficulties in the learning process.

4.5 From Descriptive to Prescriptive Analytics

The interviewees selected suggestions for suitable study paths and methods of progression as the second important functionality. Evidently, there is a need for prescriptive analytics, but this may be due to two reasons. First, in the survey responses, the courses in Haaga-Helia's Moodle were generally considered to have a bad structure and messy layout. If the course view is experienced as incoherent, it is understandable that there is a need for a tool that could pick out and organize all the important study material and assignments:

"[…] everything that is connected to the course would be on different pages and then it would progress page by page or whatever the logic would be. But it would be sequenced in a way that when you can do this, you may move forward to this [material]."

Secondly, many students were very busy with their work and family, and they expected the learning platform to somehow help them with scheduling by offering and suggesting ways to proceed with course selection, for instance. Therefore, the need for prescriptive analytics is connected with time management and self-regulation processes, as one of the interviewees described:

"I have quite a demanding job, I'm in a hurry at times. To be honest, it is sometimes challenging because I don't have the time to focus on which courses I have to work on and such. So, if there's some sort of guidance, as I said in the beginning, or recommendation available." (Interviewee 1, female)

Even though the features of prescriptive analytics were not generally seen as important as the descriptive features, the tools for guidance and steering the study process were discussed extensively by many of the interviewees. For example, when asked about using chat bots in student advising and getting further instructions, one of the students replied:

"It's essential that I get to go forward. Another thing as a blended learning student is that I do assignments and advance my studies quite late in the evenings or weekends. I don't presume teachers work at that time. If a machine can help me, then there's additional value to me." (Interviewee 4, female)

Some students were more prejudiced towards the usefulness of prescriptive analytics based on automation:

"I was thinking about getting tips or instructions based on my learning results. In principle that sounds fine. But when I think of what Spotify suggests to me based on what I have listened, it doesn't really match. I am a bit sceptical." (Interviewee 7, female)

Nevertheless, prescriptive analytics is what should be developed alongside descriptive analytics, since mere description of performance does not enhance learning. Tanes and colleagues (2011) analysed the content of feedback messages which were sent to students at risk of dropping out, on the basis of the data signals recorded in the system. They found out that the messages contained summative analysis without any instructions or feedback on the learning process or suggestions on how to overcome the challenges. Consequently, the messages had no effect on students' learning (Tanes et al, 2011).

4.6 Accurate Predictions for Optimizing the Study Process

Predictive analytics was met with a dual response: one interviewee considered it the most promising type of learning analytics where we should head for and another student thought it mainly helps teachers. Students also had mixed opinions on predictions or estimates on study time: some believed it cannot be accurately predicted because learning strategies, styles and conditions of studying vary; and others thought it could help a lot with self-regulation simply because they would be able to plan how much time they should reserve for studying. An estimate on expected reading time or time required for completing an assignment, a task or the whole course was seen as a way to make time usage more effective, since it could be easier to optimize regular studying and balance it with personal life by using free time slots efficiently. One of the interviewees suggested a predictive thermometer tool which could constantly monitor the study progression on a course level, providing alerts when the study pace is too slow, giving suggestions on what to do and demanding actions and rescheduling if deadlines seem to approach too fast. Another student speculated that grade predictions could actually help students set reasonable learning goals:

"A recommendation feature could be… when a task has not progressed… if I could set the expectation for myself, that I go for grade 4 or 5 in this course and the system predicts that grade 3 is more likely with this effort. It could recommend additional material for reading." (Interviewee 6, male)

Providing predictions on the risk of dropping out were viewed as potentially beneficial, but only if a possibility for extra guidance and academic advising was offered in connection with such predictions. It is possible that some students would take predictions in a negative way, as one of the students reflected.

5 CONCLUSIONS

Students seemed to appreciate and expect a wide range of descriptive analytics available to them. In the survey responses, the demand for time management and planning tools was significant. Getting relevant feedback on time was another major need. On the basis of the interviews, behavioural feedback contributing to descriptive learning analytics should be instantaneous and confirmative and this can be given by the learning platform or the teacher. Cognitive feedback was expected to be well timed, corrective and to some extent also suggestive, and it was expected mostly from the teacher. Supportive feedback was expected from peers. When the results are viewed in the context of the three phases of self-regulation, it is notable that learning analytics tools are expected to provide help mostly in the forethought phase (especially with planning and scheduling). The support from learning analytics in the performance phase through comprehensive monitoring and instant feedback is also appreciated and expected. The need for learning analytics tools in the self-reflection phase was less evident.

Of the three types of learning analytics dimensions, descriptive analytics was considered the most important and even fundamental. Features of prescriptive and predictive analytics were met with a more dubious attitude. The scepticism may be due to the fact that there are only a few prescriptive and predictive uses of learning analytics available. However, as Park and Jo remark, as descriptive analytics begins to be widely available, it is only natural to add some cases of predictive analytics into learning platforms and the student dashboard views (Park & Jo, 2015). Perhaps the prescriptive analytics could begin with simple recommendations and subtle suggestions with comparisons such as "students who read this material, also watched these videos…" or "students who got the best grades spent 10 hours reading this material". In any case, behaviour-based student dashboards provide important information to the students alongside knowledge-based dashboards (Auvinen et al. 2015), and sequential or procedural analysis of the student's actions in the learning process provide data that could help students find suitable strategies for self-regulation (Sedrakyan et al, 2018). Learning analytics tools should utilize a mixture of behavioural and knowledge-based data in order to provide meaningful descriptive dashboards, useful and well-timed prescriptive analytics and feedback as well as reliable predictions on learning.

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