

Addressing learner issues with StepUp!: an Evaluation

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ABSTRACT

This paper reports on our research on the use of learning analytics dashboards to support awareness, self-reflection, sensemaking and impact for learners. So far, little research has been done to evaluate such dashboards with students and to assess their impact on learning. In this paper, we present the results of an evaluation study of our dashboard, called StepUp!, and the extent to which it addresses issues and needs of our students. Through brainstorming sessions with our students, we identified and prioritized learning issues and needs. In a second step, we deployed StepUp! during one month and we evaluated to which extent our dashboard addresses the issues and needs identified earlier in different courses. The results show that our tool has potentially higher impact for students working in groups and sharing a topic than students working individually on different topics.

Categories and Subject Descriptors

H.5.2 [Information interfaces and presentation]: User interfaces;
K.3.2 [Computers and Education]: Computer Science Education

General Terms

Design, Experimentation, Human Factors.

Keywords

Learning analytics, Visualization, Reflection, Evaluation, Design based research.

1. INTRODUCTION

We consider the essence of learning analytics to be the collection of traces that learners leave behind and the use of those traces to improve learning [11]. Educational Data Mining can process the traces algorithmically and point out patterns or compute indicators [40][37]. Our interest is more in visualizing traces in order to help learners and teachers to reflect on their activity. We focus on building dashboards that visualize the traces in ways that help learners or teachers to steer the learning process [12].

We focus on deploying real tools in real courses and finding out how these tools address the learner needs. Students can have different intrinsic and extrinsic motivations to follow a course and this will affect the use of the tools. The perception on how the tools address student needs and the analysis of tool use can help us understand how we can use these tools to improve learning.

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Our courses, in which we apply learning analytics visualizations, follow an 'open learning' approach where engineering students work individually or in groups of three or four on realistic project assignments in an open way. Students use twitter (with course hash tags), wikis, blogs and other web 2.0 tools such as Toggl¹ and TiNYARM[6] to report and communicate about their work with each other and the outside world in a 'community of practice' kind of way[15][39].

In earlier work, we presented StepUp![31], a tool that empowers students to reflect on their own activity, and that of their peers, in open learning environments. In our courses, we encourage students to be responsible of their own learning activities, much in the same way as we expect them to be responsible of their professional activities later on. To support this process, StepUp! visualizes different learning traces, such as: time spent on the course, resource use (e.g. wiki and blog use) and social media use (e.g. Twitter) (see Section 3.2). Our earlier work focused on the evaluation of usability and usefulness of StepUp!. In these evaluations, we asked students to rate the usefulness of StepUp! to support awareness and reflection and to assess its usability using a standard SUS [4] questionnaire. This research showed: a) visualization of time spent on activities related to the course is a powerful trace to understand peer behavior, and b) StepUp! provides transparency about how other learners communicate. Although learners indicate that they should increase or decrease their activity, most of them did not change their behavior.

Whereas these evaluation studies provided some insight in potential usefulness and usability issues of StepUp!, we can derive little evidence from these studies about the impact of StepUp! on learning. This paper therefore focuses on precisely that topic: the potential impact with respect to issues and needs that our students have. To this end, we set up three brainstorming sessions at the start of the semester with a total of fifty-six students in multiple courses. In these sessions, students discussed their learning issues and needs. They prioritized the issues and needs derived from the brainstorming sessions by rating them. In a second step, we deployed the tool during one month. Afterwards, we evaluated to which extent StepUp! addresses the issues identified by the students at the beginning of the semester.

The remainder of this text is structured as follows: the next section presents how we performed the brainstorming sessions and the result of these sessions. How StepUp! addresses the issues identified in the brainstorming sessions is presented in Section 3. Section 4 presents the evaluation results. Related work is discussed in section 5. Conclusions and future work are presented in Section 6.

¹ <https://www.toggl.com/>

2. LEARNING ISSUES

To identify issues that students face, we carried out three brainstorming sessions with fifty-six participants in different courses during the first session of the academic year. We present details of the courses and results of the brainstorming sessions in this section. These courses were selected from the engineering study program and they share the same ‘open learning’ approach methodology. This allows us to relate the results to other factors - such as working individually or in groups and the topic of the course, rather than to different course contexts.

2.1 Multimedia course

Multimedia (abbreviation MUME) is a course that focuses on the design and implementation of mobile applications. In this course, students develop an application in HTML5, Android OS and iOS. The topic this year is mood tracking in the context of Quantified Self². Twenty master students are enrolled in this course. They work in groups of two or three.

Before introducing the topic of the course to the students, we set up a brainstorming session in which we asked the students to identify issues they experience in their studies. The result of the session was a set of thirteen problems.

In a second step, each group of students rated the problems they had, by assigning a budget of 10 points across the problems. The list of issues and their relative importance is presented in the first block of Table 1.

The following issues were rated highest: 1) detection of group members who do not work, 2) communication within the group, 3) how I distribute my time, 4) how to take decisions in the group and 5) group composition. The remaining problems got 6 points or less whereas the ones mentioned above got between 7 and 15.

2.2 Problem solving and design course

In the problem solving and design course (Dutch abbreviation PENO), students deal with the different phases of software engineering, from brainstorming, creation of scenarios and use cases to programming and evaluation of an application. The topic of this year is learning analytics. The problem solving and design course is part of the second year bachelor’s program. Two groups of eighteen students are subdivided in teams of six.

Before introducing the topic of the course to the students, we again set up a brainstorming session per group. After ten minutes, students presented the problems they had identified. Compared with the outcome of the brainstorming session in the multimedia course, nine new issues came up in the session with the first group of students in this course. In the second group, eight additional issues were identified. These issues are presented in the second block and the third block of Table 1, respectively. In addition, we included four issues that we identified in earlier research[18] (block 4 in Table 1).

The relative importance of each entry in the combined list of all issues was rated by the students in a second step. Results are presented in the PENO column of Table 1.

2.3 Master thesis students

We conducted a third case study with students working on their master thesis in our group, which focuses on human-computer interaction. The students typically do a literature study, design and

Table 1: learning issues and needs (*final selected issues, +selected in the use case, -non selected)

Issues	MUME	PENO	THESIS
Usefulness of the assignment	-	+	+
* Group member that does not work (11)	+	-	+
* Communication within the group (12)	+	+	+
* How I distribute my time (13)	+	+	+
Agreements within the group	+	-	+
Tracking (progress/effort)	-	-	-
Size of the group	-	-	+
Unclear assignments	-	+	+
Taking decisions	-	-	+
Difference in knowledge between team members	-	-	-
Group composition	+	-	+
* Alert if something goes wrong (15)	-	-	+
Too many projects/exams	-	-	+
Sharing (summaries) among students		-	+
* Motivation (14)		+	+
Too much, useless info (thick books)		-	+
Concentration (learning), distractions (facebook)		-	+
Health and personal life quality		-	+
Time lost due to transport, shopping, sports,...		-	-
Problems operating Toledo (schedule)		-	-
No pressure during the academic year		-	-
Packed days compared with other years		-	-
Lack of an effective one stop shop for info (cf. Blackboard)		+	-
Lack of a good learning environment (light, air, sound,...)		+	+
Availability of learning material when it is needed (e.g. for commuting students, or in the week-end)		+	+
Just in time mentoring and help		-	-
Not knowing what is important		+	+
Not knowing how much time is required to study a course		-	-
Fear of failing		-	-
* Lack of balance between social activities and studying (16)		+	+
Understanding how others members of my group spend their efforts		-	+
Understanding how others peers in the course spend their efforts		-	-
Transparency within the community of practice. How the members of the community interact with each other.		-	-
* To be aware which resource and tools I and others students use (17)		-	+

² <http://quantifiedself.com>

evaluate scenarios, use cases, paper and digital prototypes and release and evaluate a working version of their software. Our group counts thirteen thesis students who mostly work individually on their thesis topics.

With this group, we did not perform a brainstorming session, but we asked them to rate the issues identified by the other students. Rating results are presented in the last column of Table 1.

2.4 Results

The result of the sessions is a list of thirty-four issues, prioritized by students in three different courses.

After students rated the issues, we selected the issues that were rated high in more than one case study and that could potentially be addressed by StepUp! For instance, *motivation* is an issue that we think StepUp! can address, but *unclear assignments* and *lack*

of a good learning environment (*light, air, sound*) are not. Selected issues and needs are preceded by a star in Table 1.

In Section 5, we present results of an evaluation with students that assesses to which extent StepUp! addresses these issues.

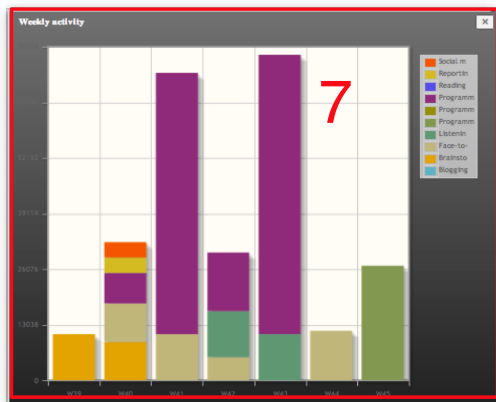
3. HOW DO WE ADDRESS THE ISSUES

In this section, we describe which traces of learner activities we track and how such traces can help us to address the learning issues presented in Section 2. Then, we present our tool and how these traces are visualized. Finally, we present how we think that our tool addresses the learning issues listed in table 1.

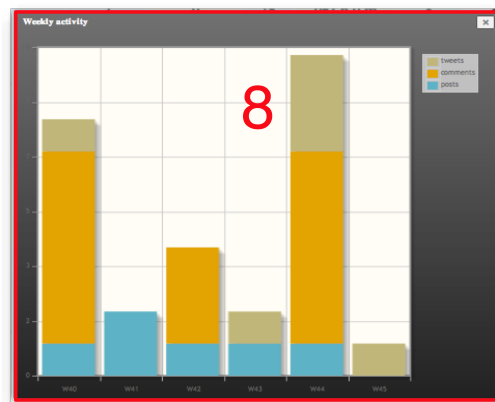
3.1 Tracked data

One of the main challenges with learning analytics is to collect data that reflect relevant learner and teacher activities [12].

posts comments twitter Toggl no contribution												
Back to the initial sorted table												
Authors	findinge	followap	moodfile	mume12	mumemood	quantify	tkindmoe	Total	Toggl	Twitter	Soc. Net.	Toggl
stijnadams	4	0	1	0	1	1	0	10	072 h 13 m	11	👤	👤
robindecroon 1	4 3	1	1	3	1	1	1	15	086 h 12 m	12	👤	👤
nielsbillen	3	0	0	2	1	0	1	7	084 h 3 m	9	👤	👤
liselotdb	0	6	0	0	0	0	0	3	073 h 7 m	5	👤	👤
jurisscheffaut	1	3	1	3	2	2	0	17	057 h 0 m	3	👤	👤
ellenvanmolle	1	6	1	4	2	2	0	15	087 h 0 m	5	👤	👤
greetrobijns	2	2	9	1	2	2	1	14	086 h 28 m	11	👤	👤
mitheyema	1	3	8	1	1	4	4	19	077 h 22 m	18	👤	👤
wel_ko	1	1	10	1	0	1	2	13	089 h 4 m	11	👤	👤
bram_gofink	0	1	0	2	1	0	1	6	050 h 58 m	4	👤	👤
mstaessen	2	2	1	8	1	3	6	20	061 h 4 m	13	👤	👤
vancampenhoutg	2	2	0	5	2	3	1	21	055 h 8 m	11	👤	👤
kimmtil	0	0	0	0	1	0	0	0	035 h 25 m	1	👤	👤
tommplot	1	0	1	0	1	0	2	7	037 h 40 m	4	👤	👤
wardcools	2	1	0	1	4	0	1	16	064 h 45 m	3	👤	👤
michaelgobbers	1	1	1	2	1	4	2	15	072 h 8 m	11	👤	👤
niktorfs	0	0	0	0	1	8	0	15	070 h 28 m	11	👤	👤
sandervoeten	1	3	1	2	1	5	0	18	070 h 10 m	8	👤	👤
jochentombal	1	0	0	1	0	0	2	10	061 h 38 m	1	👤	👤
marino_raf	0	0	1	0	0	0	5	5	072 h 37 m	3	👤	👤



Activities such as Social media, reporting, reading, programming (iOS, Android and HTML5), Listening, f2f meetings, brainstorming and blogging (respectively) are displayed on this chart.



Activities such as tweets, comments and posts (respectively) are displayed on this chart.

Figure 1 StepUp! interface

Some activities are tracked automatically: this is obviously a more secure and scalable way to collect traces of learning activities. Much of our work in this area is inspired by “quantified self” applications³, where users often carry sensors, either as apps on mobile devices, or as specific devices, such as for instance Fitbit⁴ or Nike Fuel⁵.

We rely on software trackers that collect relevant traces from ‘the Web’: learners post reports on group blogs, comment on the blogs of other groups and tweet about activities with a course hash tag. Those activities are all tracked automatically: we basically process RSS feeds of the blogs and the blog comments every hour and collect the relevant information (the identity of the person who posted the blog post or comment and the timestamp) into a database with activity traces. Similarly, we use the twitter Application Programming Interface (API) to retrieve the identity and timestamp of every tweet with the hash tag of the course.

Moreover, we track learner activities that may or may not produce a digital outcome with a tool called Toggl: this is basically a time tracking application that can be configured with a specific set of activities. Those activities can be classified based on an existing taxonomy [8] in assimilative (blogging and writing reports), communicative (twitter and comments) and productive activities (programming). We expect that this clear division between different kinds of activities will help our students to gain insight in how they and other students spend their time.

When students use Toggl, they can do so in semi-automatic mode or manually. Semi-automatic mode means that, when they start an activity, they can select it and click on a start button. When they finish the activity, they click on a stop button. Manually means that the students specify activity, time, and duration to Toggl. In this way, students can add activities that they forgot to report or edit them manually. Of course, on the one hand, this kind of tracking is tedious and error prone. On the other hand, requiring students to log time may make them more aware of their time investment and may trigger more conscious decisions about what to focus on or how much time to spend on a specific activity.

Moreover, we are also tracking other traces such as software development and participation in the wiki and it is part of our future work to include such traces in StepUp!

3.2 Visualizing the data with StepUp!

Figure 1 illustrates how the data are made available in their complete detail in our StepUp! tool: this is a “Big Table” overview where each row corresponds with a student. The students are clustered in the groups that they belong to. For instance: rows 1-3 contain the details of the students ‘stijnadams’, ‘robindecroon’ and ‘nielsbillen’ (see marker 1 at Figure 1). These three students work together in a group called ‘findinge’, the second column in the table (marker 2). The green cells in that second column indicate that these students made 4, 4 and 3 posts in their group blog respectively (marker 3). Rows 4-6 contain the details of the second group, called ‘followap’: they made 0, 1 and 1 comments on the blog of the first group (column 2) and 6, 3 and 6 posts in their own blog (column 3) respectively (marker 4). The rightmost columns (marker 5) in the table indicate the total number of comments, the total number of hours spent on the course (Toggl) and the total number of tweets.

³ <http://quantifiedself.com/>

⁴ <http://www.fitbit.com/>

⁵ <http://nikeplus.nike.com/plus/products/fuelband>

The two rightmost columns are sparklines [20] that provide a quick glance of the overall evolution of the activity for a particular student (marker 6). They can be activated to reveal more details of student activity (marker 7 and 8 at the bottom of Figure 1). These bar charts show the distribution of the activity along the weeks. The bar chart (marker 7) visualizes the time spent on the different kinds of activities, such as reading (documentation, other blogs, etc.), programming and face-to-face meetings. In this way, the students get an overview of how they have spent their time in the past week. The other bar chart (marker 8) shows the distribution of the participation (posts, tweets and comments) along the weeks. This visualization intends to trigger reflection about what the students did and why.

4. EVALUATION

We carried out a detailed evaluation six weeks into the course, based on online surveys. In the evaluation, we used four instruments, in order to obtain a broad view:

- 1) The importance of the most important learning issues (see Table 1) was rated again by students.
- 2) We asked whether students over-report or under-report time spent, enquired about their motivation and whether they thought they were doing well in the course.
- 3) Fifteen questions assessed to which extent students believed that StepUp! addressed the issues.
- 4) a SUS questionnaire assessed usability of the application.

All the questions presented in this survey use a 5-likert scale to grade importance or agreement (‘1 – not important at all’ to ‘5 – very important’ and ‘1 – strongly disagree’ to ‘5 – strongly agree’).

The survey was completed by all the students of the three courses (see Section 2). The survey results are discussed in the remainder of this section.

4.1 Analysis of the results

First, students rated the importance of the learning issues that were selected with the methodology described in Section 2. This was done to get a full picture, since the set of issues grew during the collection phase and not all students had rated all issues. The results of these questions can be seen in the grey highlighted rows of Figure 2. Afterwards, students rated statements to assess their perception on how they were doing, their motivation and how others were behaving in the course and finally, to assess whether StepUp! addressed the selected learning issues. These statements and their results are presented in the white rows of Figure 2.

In this section we discuss the results per evaluation section for the three case studies (MUME, THESIS & PENO, see Section 2). In addition, the last subsection includes an analysis of the results drawn by Google Analytics⁶.

4.1.1 Importance of the issues

The results in the boxplots for issue I1 (‘To be aware which resources and tools I and others use’) in Figure 2 are indecisive: whereas this does seem to be a somewhat important issue for the MUME students, it is much less important for the THESIS and PENO students. It is not immediately clear to us why this difference in appreciation exists. However, as MUME students usually face new challenges, learning how to develop software for iPhone and Android devices, being aware of what kind of

⁶ <http://www.google.com/analytics/>

resources are used by others can be more relevant than for PENO and THESIS students. PENO students have less freedom to choose tools to use. In addition, PENO students are bachelor students and they may feel less confident to discover and to try new resources. THESIS students share a methodology and a field (Human Computer Interaction), but their thesis topic often differs, which can be the reason that they feel less motivated to pay attention to what resources and tools others are using.

The students consider issues related to how they distribute their

time more important (median between 3.5 and 4) than I1.

Being aware that team members do not work (I3) is important for the MUME and PENO students (medians ≥ 4). This issue has not been evaluated with THESIS students because they do work much more individually.

Motivation (I4) and Being aware when something goes wrong (I5) are important for all students (all medians ≥ 4).

Communication issues are important for the students in the three

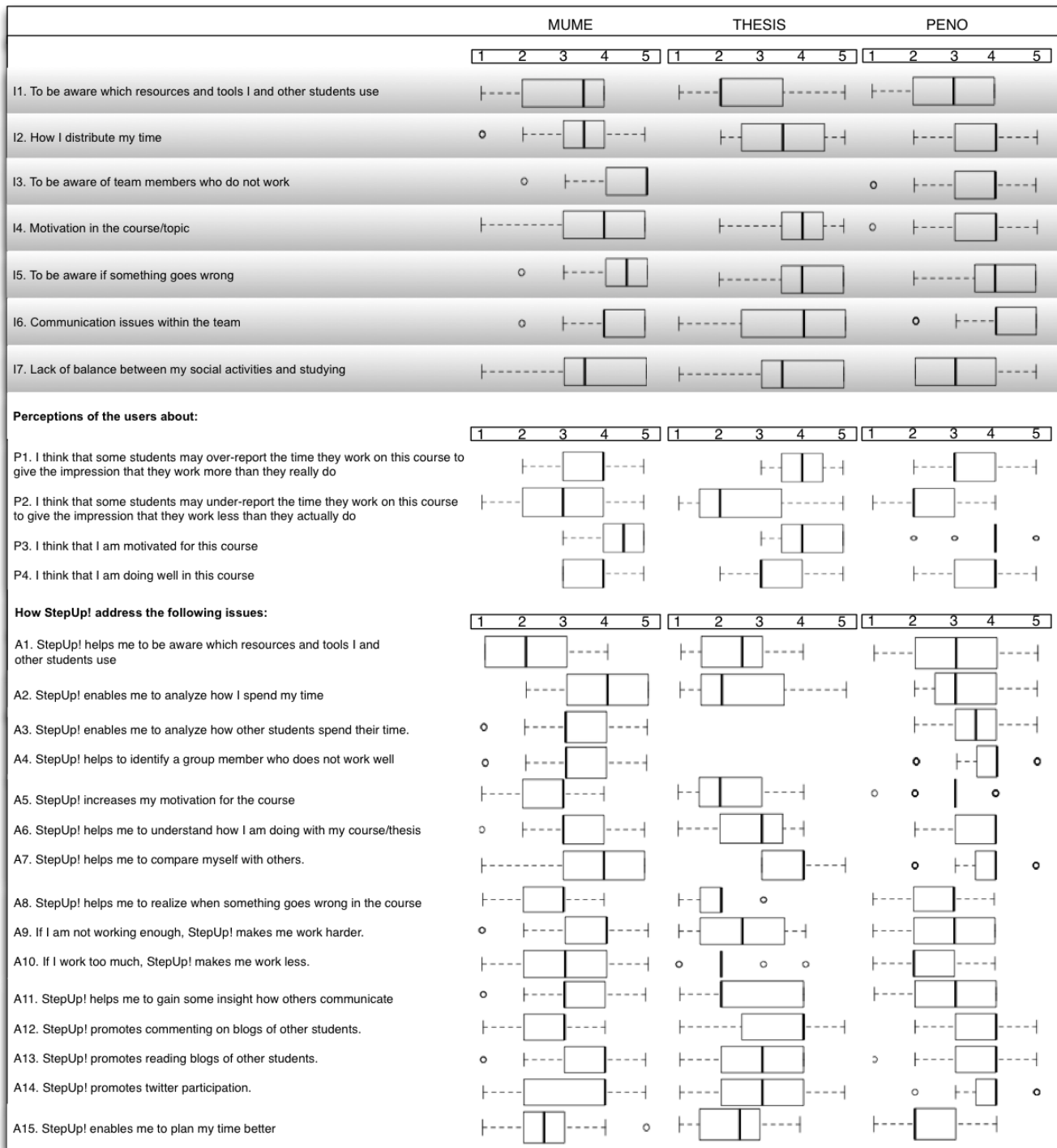


Figure 2 Results of the evaluation

courses (all medians ≥ 4). The results are a bit more spread for THESIS students. This is probably related to the fact that most of these students work more individually on their master thesis and thus care less about interacting with other thesis students.

Problems about finding a balance between social activities and studying (17) are somewhat important to the students (all medians ≥ 3 or 3.5).

4.1.2 Perceptions in the course

Among students enrolled in MUME and THESIS, there is a high perception that other students may over-report. However, PENO students are indecisive. PENO students used less our application than others. In the PENO course, most of the work is done during the lab sessions and all the groups have one member who holds the role of project manager and this fact can decrease the feeling of over-reporting.

However, all the students are indecisive when it relates to under-reporting time spent (all medians ≤ 3). This issue was included because some students pointed out that others may under-report trying to avoid that others call them grinds. Based on these results, it seems that this fear is not grounded in reality.

All of them are motivated (all medians = 4) and they think that they are doing well in the course (medians = 4) except for the thesis students. Although they are motivated, they are indecisive whether they are doing well. The fact that thesis work has to be done during a full academic year (as opposed to a semester in the PENO and MUME courses) and the non-similar topics can influence an uncertain feeling of how they are doing. However, it brings an important niche that learning analytics can try to address.

4.1.3 Issues

The students do not believe that StepUp! addresses statement A1 'StepUp! helps me to be aware which resources and tools students use' (all medians ≤ 3). This is probably related to the fact that StepUp! only visualizes blog activity and twitter use, and thus only covers a minor part of resources use in the three courses.

When we assessed if StepUp! enables students to analyze their time spent (A2), the results differ over the three courses. MUME is most positive, while PENO is indecisive and THESIS is more negative and spread. Further analysis is required to understand why this is the case: it may be that StepUp! misses more of the relevant activity in the case of the master thesis work.

StepUp! is not perceived to convincingly help students to analyze how other students spend their time (A3) (medians are 3 and 3.5).

If we compare A2 and A3 with a previous experiment [31], StepUp! has decreased its effectiveness. In this experiment, the

activities were defined with higher granularity such as programming whereas in the previous experiment were more specific activities such as first prototype. This may have affected the perception on how StepUp! helps them to understand efforts.

When asked if StepUp! allows to identify a group member that does not work well, the MUME students are not sure (median = 3), while StepUp! helps the PENO students better (median = 4). The high perception that other students may over-report time spent (P1) can influence negatively student perception on this issue.

According to statement A5, students are not convinced that using StepUp! increases their motivation (all medians ≤ 3). In this context, it is important to note that the motivation of the students for the course was high (P3 – all medians ≥ 4).

They are more positive about StepUp! helping them to assess how they are doing in the course (A6), especially the THESIS and PENO students (median ≥ 3.5). Moreover, StepUp! allows the students to better compare themselves with their peers (A7) (all medians = 4).

The students are not convinced that StepUp! helps them with being aware of course problems (A8) (all medians ≤ 3). When asked if StepUp! makes them work harder (A9) or slower (A10) if they are working not enough or too hard, THESIS and PENO students are not convinced StepUp! makes them work harder when appropriate, but MUME students are more positive (median = 4). Students are not convinced that StepUp! makes them work less (median of THESIS & PENO = 2 and MUME = 3). These results can be influenced by statement A2 that StepUp! fails helping them to understand how they spend their efforts.

Students are not convinced (median of THESIS = 2, median of MUME & PENO = 3) that StepUp! enables them to gain insights in how others communicate (A11). Regarding this issue, other visualizations such as network visualizations could improve the results. When we asked whether StepUp! makes them comment more on blogs (A12), then we see that the MUME students are not convinced (median = 3) and the THESIS and PENO students are motivated by StepUp! to comment more on the blogs of fellow students (median = 4). When assessing whether StepUp! promotes the reading of blogs (A13), we see that it helps MUME and PENO students (median = 4), but the THESIS students are not convinced (median = 3). The reason for the behavior of the THESIS students might be that they are more focused on research specific to their thesis topic, while PENO and MUME students are working on a shared topic, so the blogs of other students are more directly related to their own work. When looking whether StepUp! makes them use Twitter more (A14), we also learn that StepUp! promotes the use of Twitter more for MUME and PENO students

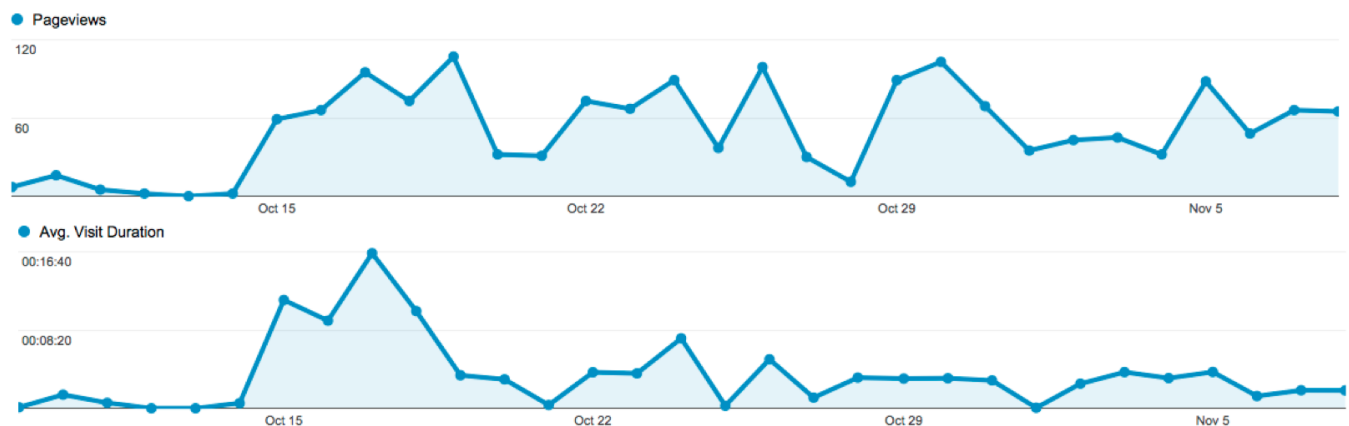


Figure 3 Google Analytics view

(median = 4), than for THESIS students (median = 3). This might be again caused by the common topic of the PENO and MUME students and thus closer social interaction.

From the rating of statement A15 ‘StepUp! enables me to plan my time better’, we learn that StepUp! does not help students to plan more efficiently (all medians ≤ 2.5). This might be because StepUp! only presents the time spent on past events and not the work that still has to be done. Nor does StepUp! provide real functionalities for planning. Our hope was that StepUp! would assist students in becoming better planners through self-reflection and sensemaking provided by the visualizations, but, at least in the perception of the students, this goal is not reached.

4.1.4 SUS questionnaire

All the students rated our tool between acceptable and good. MUME students rated the tool with 67.9, PENO students with 67.5 points and thesis with 72.1. In an earlier experiment[31], SUS scores were 77 and 82 points. Our tool has thus decreased in usability. This decrease may be due to the fact that StepUp! has been deployed for a larger group of students – which in terms of scalability also caused some problems that caused some delay updating the data on the table.

4.1.5 Use of the tool

The students have used the tool regularly as indicated by the Google Analytics view (see Figure 3). In one month, StepUp has been visited more than 850 times with an average time spent on the tool of 4 minutes.

The visits view indicates that StepUp! is more visited during the week. These visits decrease considerably during the weekend, when also students reported lower time spent on the activities. Comparing with the results in an earlier experiment, the average time has decreased around 50%. This can either be caused by or influence the usefulness perception for our tool. If students spend less time, they cannot find out the benefits of our tool. In Section 6, we present some future research plans, including the deployment of a mobile version, to better engage the students with StepUp!

5. RELATED WORK

Learning analytics consider the analysis of communication logs [14][33], learning resource use [26], learning management system logs, learning designs [24][29], as well as the activity outside of learning management systems [27][7]. The result of this analysis can be used to improve the creation of predictive models[30][5], recommendations [38] and reflection [32][23]. Since we focus on reflection, we mainly build dashboards to enable self-reflection and to enable the learner to steer the learning process or teachers to plan interventions if they are required.

In recent years, several dashboard applications have been developed to support learning and teaching. These dashboards are used in traditional face-to-face teaching, online learning and blended learning settings. Some examples are Classroom View [16] that shows current activity in a classroom, the dashboard implemented in the learning management system Moodle [28] which tracks online activities to support teachers and the educational monitoring tool based on faceted browsing and data portraits showing the current status of each student in distance education [17]. Khan Academy⁷ dashboard enables tutors to check progress of students where a table provides a goal status overview per student. For every student, a timeline shows the distribution of

achieved goals and a bar chart visualizes the time spent with different kinds of resources.

Some dashboards were developed specifically to support learners. CALMSystem [19] is an example of a dashboard that was developed on top of an intelligent tutoring system to give a learner insight into their learner model as a basis to support awareness, reflection and sensemaking. Performance indicators on different topics are visualized and can be adjusted by the learner as well. Tell Me More [22] is a commercial language learning application that tracks results of exercises as a basis to visualize progress of learners. S3 [13] is a dashboard that enables practitioners to plan interventions with students at risk. Narcissus [36] was developed to support small group work. GLASS [23], SAM [18] and Student Inspector [41] were developed to support both teachers and learners. The work presented in this paper is intended to support students and teacher reflection.

If we analyze dashboards, we find that time spent is a commonly captured trace. In addition, social interaction can help to gain insight in collaboration [9][1] and to detect isolated students [9]. Document and tool use can give effort indicators of students [18][25].

GISMO[21] also offers the possibility to detect students who do not work well. They highlight the students who have not reached a minimum number of post messages in the forum. They conclude that different learning behavior does not mean different reached goals. It can also influence to the results on the statement ‘StepUp! helps me to analyze how others spend their time’.

LOCO-Analyst[34] and SAM[18] address the issue ‘to be aware which resource I and others use’. However, SAM also struggles with analyzing time spent, because it uses logs generated by the LMS, and students claim that some activity happens outside of the LMS, so that the visualized information does not represent all their work. This fact inspires GLASS [23] that tracks all interaction within a Virtual Machine and visualizes also programming code logs.

Looking at how other researchers evaluate their dashboards, we find one longitudinal study [2] where a tool was evaluated over three years, and was found to increase retention rates. Other more limited studies focus on effectiveness [9][20][24] and perceived usefulness [1][9][17][30][33]. Most studies on effectiveness and perceived usefulness assess problems that the lecturer or the literature describes. On the other hand, other studies [3][20] reinforce the idea to ask the students what problems they have and to assess whether these problems are addressed. The work presented in this paper focuses on potential impact of StepUp! may have on issues and needs identified by our students.

6. FUTURE WORK

Now that we analyzed the reported issues by the students, we would like to focus on one important factor of learning: motivation. Although our students are motivated in our courses (see 4.1.2), we see from the results of the evaluation that we are failing addressing some issues that may affect motivation.

Thesis students do not know whether they are doing well in the course (section 4.1.2.) and this is an important factor for the motivation of the student [42]. We expected that StepUp! could address this issue by enabling comparison between peers, but StepUp! does not help understand how peers as well as themselves spend their time (section 4.1.3). Furthermore, StepUp! does not motivate them to increase their social interaction blogging, commenting and tweeting.

⁷ [http:// www.khanacademy.org/](http://www.khanacademy.org/)

In order to address the reported issues, we will focus more on generated artifacts and student motivation . To this end, we are currently enriching StepUp! with gamification aspects: StepUp! will again track blogs, comments, tweets, and, in addition, bookmarked resources. We will define a series of rules in order to reward students with badges for positive behavior. Badges will be strongly linked to the activities of the course in order to increase awareness of student progress in the course.

However, gamification approaches can have negative effects [42]. By making available an overview of achievable badges, we hope to increase student awareness about what we expect from them. In this way, we expect to deploy a more goal-oriented approach improving perception on how students are doing in the course .

Visualizations such as progress bar chart can also reinforce the idea of goal-oriented approach and activity streams increase the awareness of and engagement to the course. Thus, these approaches will also be integrated in the next version of our tools.

7. CONCLUSIONS

We have set up a series of brainstorming sessions to gather requirements and to identify the most important issues for students. As explained in Section 3, we considered which functionalities of StepUp! could potentially help to address the issues.

The general conclusion is that our tool has potentially higher impact for students working in groups and sharing a topic such as PENO and MUME than students working individually on different topics. However, overall, students are not that convinced of the added value of StepUp!.

Thus, we believe that this study helps to point out that demonstrating the relevance of learning analytics dashboards like StepUp! is a complex undertaking. We strongly believe that more critical evaluations of the actual use of such tools are required. Student perceptions of added value are not the only criterion, but certainly a most important one!

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