Time will tell: The role of mobile learning analytics in self-regulated learning

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Time Will Tell: The role of mobile learning analytics in self-regulated learning

Bernardo Tabuenca, Marco Kalz, Hendrik Drachsler, Marcus Specht
Welten Institute, Open University of the Netherlands, Netherlands

Abstract. This longitudinal study explores the effects of tracking and monitoring time devoted to learn with a mobile tool, on self-regulated learning. Graduate students (n=36) from three different online courses used their own mobile devices to track how much time they devoted to learn over a period of four months. Repeated measures of the Online Self-Regulated Learning Questionnaire and Validity and Reliability of Time Management Questionnaire were taken along the course. Our findings reveal positive effects of tracking time on time management skills. Variations in the channel, content and timing of the mobile notifications to foster reflective practice are investigated, and time-logging patterns are described. These results not only provide evidence of the benefits of recording learning time, but also suggest relevant cues on how mobile notifications should be designed and prompted towards self-regulated learning of students in online courses.

Keywords. Self-regulated learning; Time management; Learning analytics; Mobile support

1 Introduction

One of the main challenges in the field of Technology Enhanced Learning is the recognition of the activities and contexts of learners [1]. Lifelong learners constantly change their learning context, location, goals, environments, and also learning technologies. Lifelong learners have to combine their professional activities with learning activities and must engage simultaneously with family times to ensure a balance of adults' responsibilities, overall wellbeing and their personal development. In this scenario a student taking part in an online course might start the day during travel with the reading of the course textbook, continue at work joining an online discussion of a specific problem during the coffee break, and finish in the evening watching video contents of the course while laid on the sofa during commercial breaks on TV. These short learning episodes during one day are a representative picture of lifelong learning as a whole. Learners are active in scattered moments, in different learning contexts, in different learning formats, and with different learning technologies.

Despite a growing body of research predicting [2], describing [3]–[5], or providing suitable guidance on patterns of behaviour to support the learning process in online learning environments (e.g. in Learning Management Systems [6] or in MOOCs [7]), little is known on how students devote their time to learn across contexts beyond the boundaries of the virtual platform.

Longworth [8] stresses the importance of lifelong learning for the twenty-first century enumerating six barriers to lifelong learning as important action points to be addressed by research and developmental activities: (B1) lack of personalisation; (B2) time and place; (B3) lack of facilities to study at home; (B4) fragmentation in learning experiences; (B5) health and age; (B6) lack of finance. More recently, Kalz [1] mapped these barriers to technologies suggesting the adoption of *mobile and contextualized learning* as key solution towards dismantling barriers B1, B2, B3 and B4.

Indeed, the mobile device is probably the only artifact co-existing with the learner in all scattered learning moments and learning contexts throughout the day. Hereby, we propose using personal mobile devices to log the time devoted to learn as a suitable approach to obtain accurate measures on how do students enrolled in online courses learn independently of the material they are using (e.g. course book, paper notes, tablet, computer), independently of the location (e.g. waiting times, commuting, workplace, home) and independently of the duration of the learning session (e.g. 1 to n minutes).

1.1 Mobile support for self-regulated learning

Learning to learn is one of the eight key competences for lifelong learning [9]. It is described as the ability to pursue and persist in learning, to organise one's own learning, including through effective management of time and information. This competence is closely bound to the concept of self-regulated learning when defined as students' proactive actions aimed at acquiring and applying information or skills that involve setting goals, self-monitoring, managing time and regulating one's effort towards learning goal fulfilment [10], [11]. In this manuscript personal mobile devices are instantiated as instruments to log and keep track of the time devoted to learn as a measure to foster self-regulated learning in online courses.

This study introduces the following features with the aim to investigate variations and best practices in mobile and contextualized learning as an approach to dismantle the barriers (B1-B4) for lifelong learning [1]:

Psychology of notifications.
Recent work shows that simple notifications via SMS are useful to promote self-regulation [12] and reflective practice on meta-learning [13]. Tabuenca et al. [14] propose sampling of experiences in personal mobile devices to foster awareness on personal learning preferences towards building an autobiography as a learner. The authors classify notifications based on the "timing" when the notifications can be triggered: (1) scheduled-based notifications (or interval-contingent [15]) when the notifications are triggered following a time pattern. E.g. everyday at 10 am; (2) random-based notifications (or signal-contingent), when the notifications are triggered at any moment not following a time pattern; (3) event-based notifications, when the notifications are triggered on the accomplishment of an event happened in the context of the student. I.e. the student reaches a specific location, there is a new instruction posted by the teacher at the course platform, or the whether conditions have changed. Likewise, the authors classified notifications according to the "format of the content" (e.g. text, audio, video) providing cues on which prompt might better fit to each specific context. More recently, two studies [13] analyse the effects from the variation of these variables (timing and content) on learning, envisioning a higher knowledge gain and motivation in the group of students assigned with the least complex interactions, and raising important research questions for future research on mobile notifications. Based on these conclusions, our assumption is that notifications might trigger better results in self-regulated learning when they are triggered in the morning (scheduled-based [14]) so students can better plan ahead their learning day in contrast to messages received in the evening or in unexpected moments throughout the day (random-based [14]). The current study therefore, postulates positive effects of sampling time-logs in self-regulated learning.

- H1: There is a positive relationship between logging and monitoring study-time, and self-regulated learning.
- H2: Notifications delivered in the scheduled time-basis produce higher scores in self-regulated learning than notifications delivered on randomized time schedules.

Learning analytics.

Learning analytics are driven by the collection and analysis of traces that learners leave behind [16]. It can help to understand and optimise the learning process and the environments in which it occurs [17]. Until now, learning analytics are mostly feedback to the users in web-based learning dashboards [18]. Those dashboards can support raising awareness and reflection of individual and peer performance, suggest additional learning activities or content and therefore can have an impact on the learning behavior. For instance, monitoring the state in a learning activity can motivate the learner towards the accomplishment of a learning goal. This cognitive process has been defined as "self monitoring", and "understanding how to learn" [19]. Personal mobile devices can be used as instruments to collect and monitor learning analytics towards self-regulation. There are little studies about mobile and ubiquitous learning analytics tools so far [20], [21]. But in fact mobile devices are especially suited for self-monitoring and reflection, as the learners have them with them and can therefore reflect about their learning progress on demand and in different environments than their actual study location.

Indeed, learning analytics can be served in every feature phone via SMS notifications, or in powerful smartphones via richer visualizations or statistics. Hereby, we propose the use of both channels with the aim to provide learning context to every student beyond the learning platform. The conclusions from Tabuenca et al. [13] suggest that notifications fostering reflective practice should contain messages that spark the attention of the student rather than repeated messages with the same content. Indeed, the more customized the learning analytics are, the more relevant will be for the student. The current study therefore hypothesizes better scores in self-regulated learning when notifications contain feedback with learning analytics for self-regulation in contrast to notifications containing generic tips for self-regulation.

- H3. Notifications containing learning analytics produce better scores in self-regulated learning than notifications containing generic tips for self-regulation.

Seamless learning.
This study aims at facilitating a mobile tool that can be smoothly integrated by any student in his daily learning routine. The concept of seamless learning is to make the transitions between the different learning situations and context as smooth as possible [22]. The proliferation of wireless-network technologies facilitates the scaffolding of seamless learning spaces as an approach for continuing learning experiences across different scenarios. Previous work [13] stresses the significance of students' digital competence and familiarity with mobile technology, as key aspects to take into account when sampling learning experiences on mobile devices. The diversity in competence is more notable when students have to deal with non-personal mobile devices for which the time to accomplish the learning task oscillates more remarkably. As a consequence of their results [13], the authors suggest providing tools with simple interactions, using personal devices and in long-term studies. In the current research, two different mobile tools are used to investigate which patterns (or lack thereof) can be found in the way students learn and log their study-time. This study hypothesizes the following statements.

- H4: There are specific patterns in how students learn and log their study-time.
  - a) What patterns can be highlighted in the way students study and report their time?
  - b) Do notifications motivate students to study and report their time in the same moment they receive them?
  - c) Is there any correlation between the number of time-logs, the duration of the time-logs and the final grades obtained at the final evaluation
- H5: There is a negative correlation between the complexity of a tool for mobile learning support and the ability to integrate it in daily routines.

2 Method

2.1 Participants

A total of 89 students enrolled in online courses from two different universities in the Netherlands were invited to participate in the study. Data were collected using online forms from three different courses, namely, Psychology (C1) and two courses of Geographical Information Systems (C2 and C3 respectively). Participants in the study finally involved 36 students (17; 10; 9) that voluntarily signed the consent form, completed the pre-questionnaire and logged learning time during the course. The students recorded 1456 time-logs in the three courses: 1030 time-logs (70.74%) in C1; 356 time-logs (24.45%) in C2; 70 time-logs (4.80%) in C3. The duration of the courses was 16 weeks, 9 weeks and 6 weeks respectively.

2.2 Materials

The experiment has used the following tools and materials:

LearnTracker Backend.

The LearnTracker Backend is accessible for the community as a cloud based solution in which teachers and instructional designers can create courses and deploy them to mobile devices. The LearnTracker Backend was released in September 2014 hosting three active courses. This system hosts and manages the master database. Additionally, the LearnTracker Backend encompasses a set of JAVA RESTful webservices that implement an open API with the aim to provide support across mobile clients (i.e. iOS, Android, Windows, Blackberry ...) and browsers (Chrome, Safari…). Both database and webservices are deployed and running in Google App-Engine. The LearnTracker Backend[i] is able to request and response messages in standard JSON format via HTTP (Figure 1).

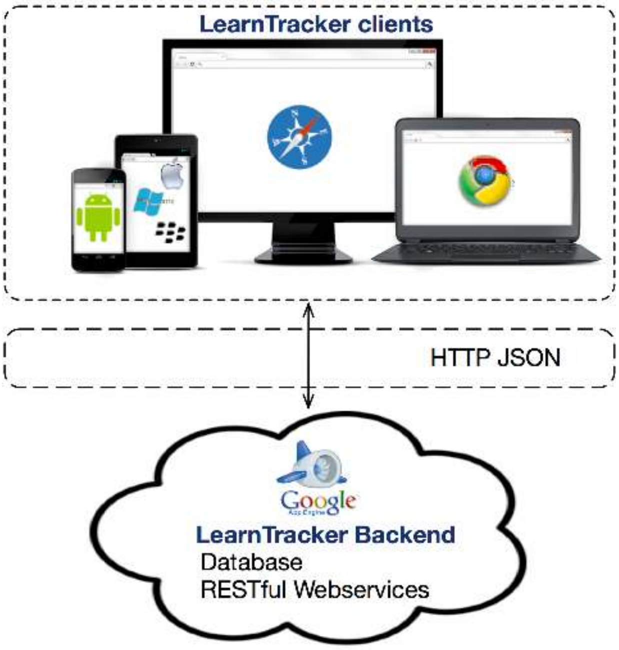


Fig. 1. LearnTracker's outline

Database model.
The LeanTracker Backend features the following tables (Figure 2):

- Subject. This table includes the information that defines the yardstick in a course (Figure 3a). The field *subject_desc* is the course identifier (e.g. "NS2322"), *subject_task_desc* is a short description of the assignment within the course (e.g. "2.2 Geometry"), *subject_task_alternative_desc* is an extended description of the assignment (e.g. "Getting to know ArcGIS and Georeferencing"), *subject_task_date_start* is the date in which the assignment is scheduled to start in milliseconds (e.g. "1418014800000" would be the 8th December of 2014), *subject_task_time_duration* is the duration of the assignment as foreseen by the teacher in milliseconds (e.g. "7200000" would be 3 hours), *subject_task_level* is a numeric field aimed to build hierarchies within the assignments (e.g. "0" would be the most generic level in the hierarchy. "1" would be one level nested within the generic level), *subject_task_order* is the order in which the assignments are presented in the yardstick (e.g. the item "2.2 Geometry" in Figure 3a has order "3" in the sequence list). The records in this table are inserted when a new course is created or updated. From the course kick-off on, this table is used only for reading from the LearnTracker clients.

- User. This table includes the information that identifies the students enrolled in a course. The field *subject_desc* is the course identifier in which the student is enrolled (e.g. "NS2322"), *user_name* is the name of the student (e.g. "*Natalia García"*), *user_type* is a numeric field aimed to cluster students in groups (e.g. "0" might be the control group, "1" might be the treatment group). The records in this table are only inserted when a new course is created and new students are registered for the course. From the course kick-off on, this table is used only for reading when students log in from their LearnTracker clients for the first time.
- Activity. This table hosts the timestamp and duration of the learning activity for which the students record their time. The field *id_user* is the name of the student, *id_subject* is the assignment identifier for which the student registers time, *activity_date_checkin* is the timestamp in which the student recorded the learning activity in milliseconds (e.g. "1431164340000" is the "17/09/2014 at 5:39 AM)", *activity_date_checkout* is the timestamp in which the student finished the learning activity in milliseconds, *activity_date_latitude* and *activity_date_longitude* are the coordinates in decimal degrees where the student registered the activity (e.g. reading at La Plaza del Fuerte in the city of Calatayud would be "41.3535300" and "-1.6431800" respectively, "activity_record_mode" indicates whether the student is recording the activity using the synchronous option from LearnTracker client, i.e. value "0" means that the student clicked on the start button when started the activity (see play in Figure 3b) and afterwards clicked the end button when he finished the learning activity (see stop in Figure 3c). The asynchronous option represented by the value "1", means that after finishing the learning activity, the student records the duration of the activity (Figure 3b, selecting the time in the slider and using fast forward button). This table is used for reading when the LeanTracker client loads the data from the backend as well as for writing for each activity recorded.

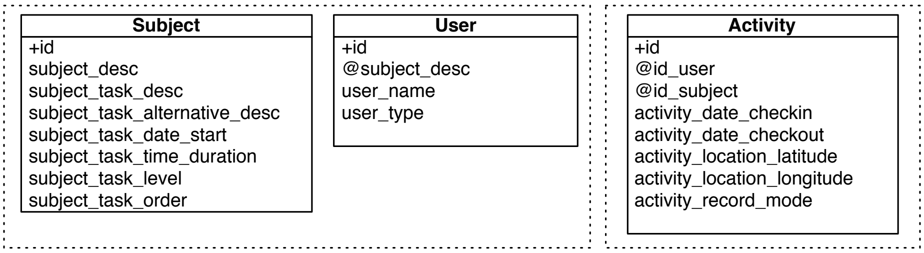


Fig. 2. LearnTracker Backend's database model

Webservices.
The LearnTracker Backend features a set of RESTful web services with the aim to provide access to the database from any device connected via HTTP to the Internet. An API has been implemented and released to facilitate the development of further new clients (i.e. iOS, Windows, Blackberry, browser version). The API[ii] and its commands are described in Appendix A.

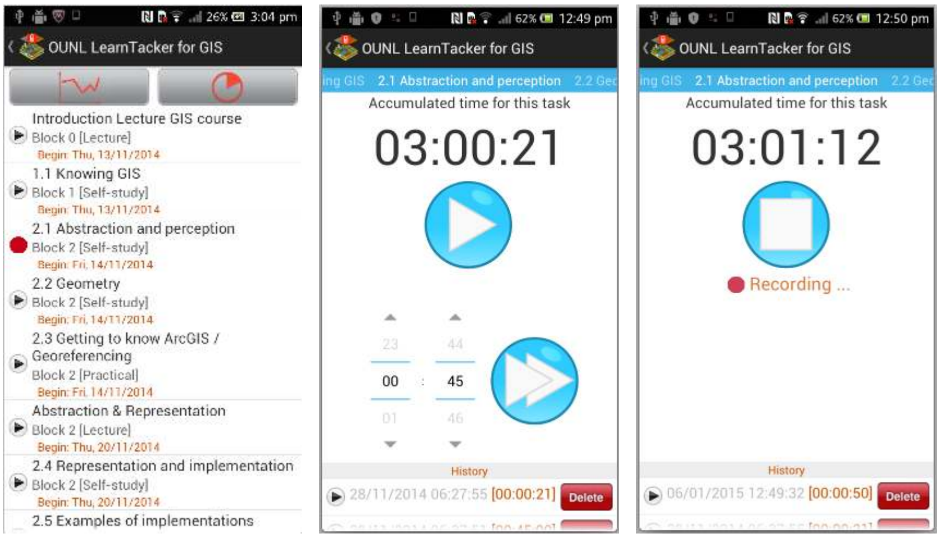
Mobile clients.

LearnTracker for Android.
The LearnTracker client is an adaptation from the NFC-LearnTracker[iii] [23], [24], a standalone application developed for NFC-enabled devices released in March 2014[iv]. The LearnTracker has been designed on the seamless notion that lifelong learners can study in a variety of scenarios switching from one scenario or context to another easily and quickly, using the personal device as a mediator. Students can use their personal mobile device to record their study-time across context. Based on these time logs, suitable visualizations with learning analytics can be served with to provide feedback on the time devoted to each learning activity. The LearnTracker contrasts the NFC-LearnTracker in the following features:

- Learning goal definition. Teacher created goals vs. learner created goals. LearnTracker provides mobile support for students enrolled in online courses in which the learning goals are predefined by teachers or instructional designers. Most of the times, courses are planned clustering the content in activities, estimating when the activity should be started and the quantity of time that should be devoted to accomplish the learning goal. Teachers define learning goals in

LearnTracker (Figure 3a) based on the yardstick of the subject, in contrast to NFC-LearnTracker in which the learner defines his personal learning goals based on own motivations and circumstances.

- Data storage. Remotely stored data vs. locally stored data. Courses deployed in LearnTracker are retrieved from the remote database at LearnTracker Backend. Likewise, time-logs are also recorded in the backend. Nonetheless, NFC-LearnTacker is a standalone app displaying learning goals that are previously created by the student in a client database. Time-logs are also recorded in the database of the mobile device. This feature implies remarkable differences in two aspects: (1) Connectivity. LearnTracker requires Internet connection to store the data whereas NFC-LearnTracker does not. (2) Privacy. Time-logs in LearnTracker are recorded in a public remote database in contrast to NFC-LearnTracker in which the data is stored in private mobile device.
- Interaction. Friction vs. frictionless interactions. At the present time, tagged objects are widely accepted and the prominent adoption of Near Field Communication from the main mobile vendors in the last months (i.e. Apple from iOS 8 or Samsung from Android Kit Kat) has boosted this technology from an innovator to an early adopter phase. Mobile NFC technology has been increasing implemented in different learning contexts in the last years [25]. Nevertheless, (as to date March 2015) the majority of the students do not own an NFC-enabled mobile phone. Students using NFC-LearnTracker tap on NFC-tags (i.e. attached to books, etc.) to record when they start and stop studying on a specific activity. Students using LearnTracker click play every time they start studying an activity (Figure 3b), and tap stop when they finish working on the activity (Figure 3c).



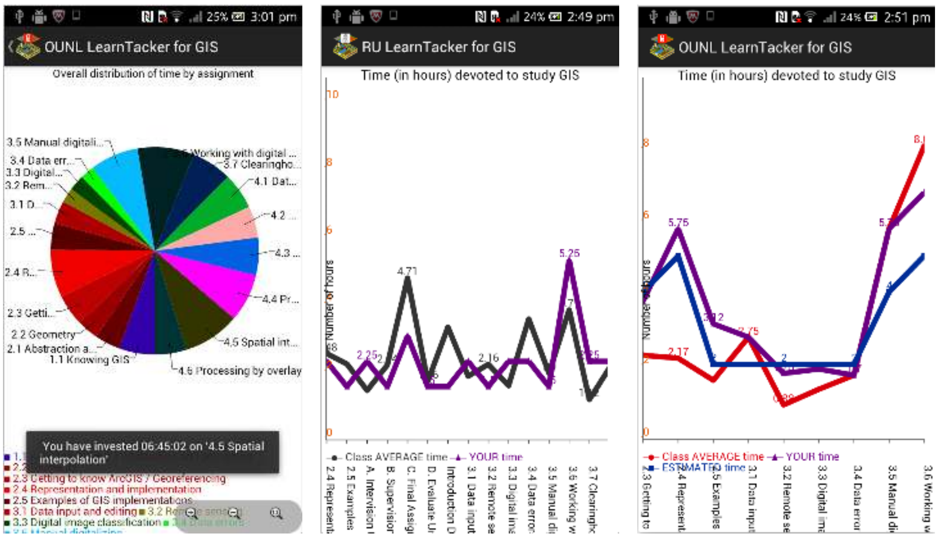
a) Yardstick comprising the activities scheduled in the GIS course

b) Check-in: Tap to start learning activity "2.1 Abstraction and perception"

b) Check-out: Tap to stop learning activity "2.1 Abstraction and perception"

Fig. 3. LearnTracker client for Android

- Learning analytics type. Personal vs. social. Learning analytics are measures reporting on data about the students and their context for purposes of understanding learning and the environments in which it occurs [26]. NFC-LearnTracker features learning analytics monitoring patterns and the behaviour of the student (i.e. Figure 4a). LearnTracker additionally provides social learning analytics contrasting the time devoted by the student with the time devoted by his colleagues at the classroom (Figure 4bc), as well as the time initially estimated by the teacher (Figure 4c).



a) Piechart. Time devoted by a student to the learning activities in a course.

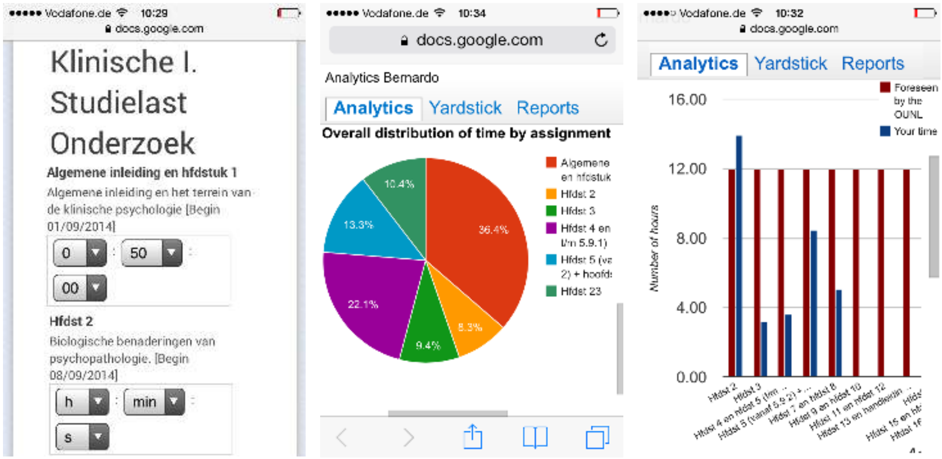
b) Linechart. X-axis illustrates activities in a course. Y-axis represents the number of hours devoted to study. My time (violet line) vs. My colleagues' time (black line)

c) Linechart. X-axis illustrates activities in a course. Y-axis represents number of hours devoted to study. My time (violet line) vs. My colleagues' time (red line) vs. My teacher' estimation (blue line)

Fig. 4. Learning analytics in LearnTracker

Multiplatform web interface.

The multiplatform web interface was designed with the aim to enrol those students that did not own an android device in the experiment. A mobile adapted online form was created based on the yardstick of the course so students can log their time via mobile web browser (Figure 5a). The results spreadsheet was extended to present visualizations summarizing the recordings every time they recorded time: a pie chart showed the overall percentage of distribution of time by assignment (Figure 5b); a barchart showed the time the had devoted to each assignment in contrast to the time initially estimated by the teacher (Figure 5c).



a) Yardstick

b) Piechart. Time devoted to each learning activity

c) Barchart. My time VS time initially scheduled by the teacher

Fig. 5. Multiplatform web interface

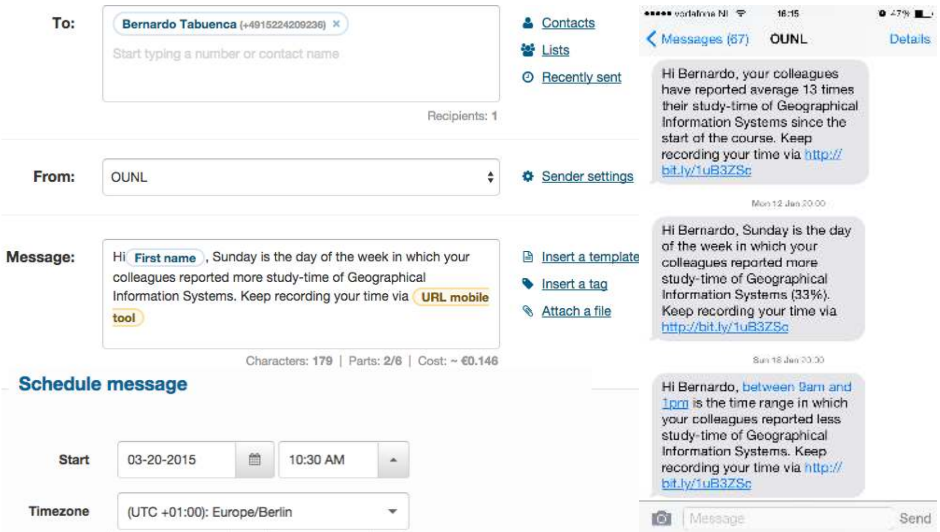
Notifications and SMS broadcasting tool.

The notifications broadcasted to students were designed based on lessons learned and conclusions taken from previous research [13], [14]. Hence, the list of notifications offered to the students in this experiment (see list in Appendix B) aimed at covering the following four key requirements:

- *Notifications should be customized and non-repetitive*. Tabuenca et al. [13] offered SMSs with repeated and structured introspective episodes meant to make learning visible. The authors propose further research prompting customized and non-repetitive notifications rather than regular notifications with similar content to keep attracting the attention of the user during the course. Hereby, the notifications designed in this experiment included their name to capture their attention as well as useful non-repetitive content (tips & analytics), and finally the link to their personal logging tool.
- *Notifications should trigger something and clearly prompt the action to do*. The notifications designed in this experiment offered explicit signals to students on what to do next towards better time management and self-regulation (see Appendix B. i.e. plan ahead; focus; record your time.).

- *Notifications should stimulate curiosity*. The notifications designed in this experiment aimed at attracting users to learn more on time management offering riddles to students so they could stop and reflect what they might find if they would do so (i.e. "Sunday is the day of the week in which your colleagues reported more study-time"; "Your colleagues are reporting an average of 4 hours 20 minutes of study-time per week").
- *Notifications should be well timed to produce an instantaneous emotional effect on what to do next*. Nowadays, smartphone users are constantly receiving notifications from applications that provide feedback, reminders, recommendations or announcements, hence it is important to offer suitable notifications (in time, in number of instances and the frequency) so the emotional effect keeps active along the course. Previous studies offering notifications in-action (during the course) and on-action (after the study session) highlight the importance of offering notifications in a suitable moment so students are not overwhelmed and loose the interest on the signals [13]. In this study two notifications per week were broadcasted aiming the following three purposes: a) plan ahead your learning day, thus a set of notifications were scheduled early in the morning; b) summarize and reflect how was your learning day, thus a set of notifications were scheduled late in the evening; c) sampling of experiences in context, thus a set of notifications were scheduled randomly during day-time.

Based on these four requirements, an online SMS-broadcasting platform[v] was selected. Notifications were customized uploading the data from the students (name, phone number, mobile tool). Afterwards, a template was created for every notification so the customized data was inserted within the tags (See Appendix: {First name}{URL mobile tool}). Finally, the notifications were scheduled and broadcasted based on the previously defined time patterns (Figure 6).



a) SMS management tool b) Notifications generated out of the templates

Fig. 6. SMS broadcasting tool

2.3 Design of the experiment

The design of this experiment consisted in repeated measures of the dependent variables “validity and reliability of time management” and “self-regulated learning” in which all the students had the same treatment (See Figure 7). The treatment was varied after every measure based on the independent variables of “timing” (scheduled and randomized) and “content” (generic tips, learning analytics) of the notifications. Additionally, measures of usability and perceived usefulness of the experiment were taken during the course. The courses C1, C2 and C3 varied in their duration (16, 9 and 6 weeks respectively), the duration of the treatments (4, 3, and 2 weeks respectively), and the treatments implemented (T1-T3, T1-T3, and T1-T2).

This study was aimed also to explore which analytics might better fit depending on the distribution working hours scheduled by the teachers. Hence, the treatments implemented for the courses C1, C2 and C3 varied the chart visualizations provided via LearnTracker client. On the one hand, the teacher in C1 designed the yardstick considering even number of hours for each one of the weeks in the course (x working hours per week). Hence, barcharts (See Figure 5c) were featured in the first implementation of the experiment (4 months). On the other hand, the teachers from C2 and C3 designed the yardstick scheduling a specific number of working hours per assignment. Additionally, a social component was added in C2 so students could contrast their study-time with the average study-time by the students enrolled in the course (See “Class average time” in Figure 4b). In the last implementation (C3), the three components of study-time were integrated within the same visualization (i.e. study-time recorded by the student, average study-time recorded by the all the students, and study-time initially scheduled by the teacher). Hence, linecharts with 3 variables were featured in C3 (See Figure 4c). The piecharts were featured in C1, C2 and C3 with the aim to monitor the overall time devoted by assignment (See Figures 4a, 5c).

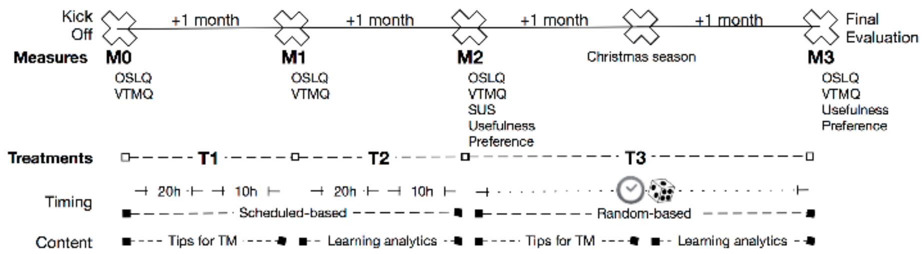


Fig. 7. Experimental design for the course 1 (C1)

2.4 Measure instruments

Self-regulated learning.

Previous research has indicated that self-reported measures of self-regulation have been unreliable as over-estimates of self-regulated learning [27]. The Online Self-Regulated Learning Questionnaire (OSLQ) has been evaluated with an acceptable measure of self-regulation in the online and blended learning environments [28]. The OSLQ consists of six subscale constructs including “environment structuring”, “goal setting”, “time management”, “help seeking”, “task strategies”, and “self-evaluation”. The OSLQ is an adaptation of the Motivated Strategies for Learning Questionnaire [29], [30] to evaluate self-regulation in online learning environments. The OSLQ is a 24-item scale with a 5-point Likert-type response format having values ranging from strongly agree (5) to strongly disagree (1).

Validity and reliability of time management.
The aim of this research is investigating on the whether the intervention proposed would produce positive effects in self-regulated learning with a special focus on how learners manage their time. Hence, the Validity and Reliability of Time Management Questionnaire (VRTMQ) [31] was included in the measures. The VRTMQ consists of 3 subscale constructs, including "time planning". "time attitudes" and "time wasters". The VRTMQ is 27-item scale with a 5-point Likert-type response format having values: 1) always; 2) frequently; 3) sometimes; 4) infrequently; 5) never.

Time patterns.
The time-logs recorded by the students are used to analyse and to understand patterns describing how they learn along the day, along the week and during the whole course.

Complexity of the mobile tools.
Three indicators are taken to contrast the complexity of the tool:

(1) Usability and (2) Learnability. The System Usability Scale (SUS) [32] was used to evaluate both mobile tools. The SUS scale consists of ten questions with a five-point Likert scale clustered in learnability and usability subscales. Based on the current literature, a SUS score above 68 (SD: 12.5) is rated as above average usability score. The analysis of the results has followed the recommendations from Sauro [33] so they can be mapped and benchmarked against 446 previous studies and 5000 individual responses.

(3) Interaction. Recent work suggests a set of interaction guidelines in designing mobile learning tools to achieve efficiency, effectiveness and satisfaction of learning [34]. The authors stress the importance in the number of clicks, scrolls or swipes to navigate within the app, as well as the quantity of information contained per page "*Extensive scrolling and the number of clicks should be well thought. The height and width of the display area should not exceed the screen size. Long pages should be segmented into smaller chunk and provide effective mechanism to view and jump to the desired page whenever users initiate an action or click on it*". Hence, the researchers have explored both mobile tools with the aim to identify shortcomings and to report lessons learned regarding the interaction with the mobile tools.

2.5 Procedure

The authors contacted online instructors via email asking for participation in an experiment that aimed at fostering self-regulated learning of students using technology. Three instructors accepted the invitation and granted permission for the researchers to advertise the experiment and provide instruction in the online platform. Afterwards, the researchers collected the information about the yardsticks of the courses from the teachers (activities, start dates and estimated durations). This data was deployed in the database hosted in the backend making it available to the mobile clients.

The day of the kick-off, the experiment was presented to the students to estimate how accurate estimations by instructional designers are with regard to the time needed to accomplish each learning activity scheduled in a course. Hence, the researchers alerted students on the importance of making truthful time-logs stressing the correlation between the accuracy of their time-logs and the quality of the feedback the students would retrieve in the learning analytics. The teachers clarified that the number of time-logs recorded would not affect their grades and participants were assured that their responses would remain anonymous and confidential. Both mobile tools were demoed and students were invited to voluntarily select the one they might find handier based on their preferences and their mobile features.

Concurring with the course kick-off, the mobile tools used in this experiment were presented in a technology enhanced learning workshop[vi] that gathered teachers and researchers with the aim find suitable combinations between theory and practice. The feedback collected in this meeting was useful to identify potential uses of the information collected with these tools and which chart visualizations matches better to each scenario. These conclusions are further analysed in the discussion section of this manuscript.

2.6 Data analysis

Questionnaires data were imported from the survey-platform into MS Excel format and then exported and analysed using R Studio (v0.98.1102). Time-logs data were exported from the backend to JSON format, then converted to comma-separated-files and imported into MySQL tables. Based on the proposed research questions, SQL-queries were created and the results were finally analysed with R Studio.

Internal consistency

The scores obtained from OSLQ demonstrated adequate internal consistency of scores with α = .80. Nunnally [35] has suggested that score reliability of .70 or better is acceptable. When examining the internal consistency of scores by subscale (Table 1), values for Cronbach alpha ranged from .76 to .83 revealing sufficient score reliability for "goal setting", "environment structuring" and "time management". Nevertheless, values for Cronbach alpha ranged from .41 to .50 revealing insufficient score reliability for "self-evaluation" and "task strategies". "Help seeking" was accounted as reliable due to its close approximation to the acceptance value.

The scores obtained from the VRTMQ demonstrated adequate internal consistency of scores with α = .89. When examining the internal consistency of scores by subscale, values for Cronbach alpha were .92 revealing sufficient score reliability for "time planning". Nevertheless, values for Cronbach alpha ranged from .30 to .56 revealing insufficient score reliability for "Time attitudes" and "Time wasters".

Table 1. Internal consistency of OSLQ and VRTMQ (n=52). *Internal consistency (α >=70)

Scale	Subscale	Num. of items	Cronbach's Alpha
OSLQ	Goal setting	5	.83*
	Environment structuring	4	.78*
	Time management	3	.76*
	Help seeking	4	.69*
	Self-evaluation	4	.50
	Task strategies	4	.41
	Total OSLQ scale	**24**	**.80***
VTMQ	Time planning	16	.92*
	Time attitudes	7	.56
	Time wasters	4	.30
	Total VTMQ scale	**27**	**.89***

A Shapiro–Wilk test was conducted with the aim to confirm the normal distribution assumption towards performing an analysis of variance (ANOVA). The p-values lower than 0.05 and the observations of the Q-Q plots conclude that the samples (goal setting, environment structuring, time management and time planning) deviate from normality .

3 Results

Most of the results presented in this section correspond to the course C1. The data obtained from courses C2 and C3 cannot be aggregated to the analysis of C1 for differences in tooling (See section "Design of the experiment"), duration of the courses, and consequently the duration of the treatments. The data collected from C2 and C3 cannot be analysed separately, as there were not enough students that completed the four questionnaires (M0-M3). The measure initially scheduled in Christmas season was discarded because most of the students did not reacted to the notifications to complete the questionnaire in this period (See Figure 7).

3.1 Impact of logging/monitoring time in self-regulation

The data obtained in the course C1 is used to evaluate the first hypothesis (H1). As the samples for goal setting, environment structuring, time management and time planning deviate from normality, alternatively to ANOVA, a Friedman's ANOVA test was performed (Table 2). This test is used for testing differences between conditions when there are more than two conditions, the same participants have been used in all conditions, and the samples are non-normally distributed.

Table 2. Means for the course C1 (n=13). 5) Strongly disagree; 4) Disagree; 3) Neutral; 2) Agree; 1) Strongly agree; (*Friedman's ANOVA significance: $p < .05$)

		Means				Friedman's ANOVA
Scale	**Measure**	**M0**	**M1**	**M2**	**M3**	**p-value**
OSLQ		2.67	2.56	2.44	2.55	.46
	Goal setting	2.46	2.00	2.03	2.00	.20
	Environment structuring	1.87	1.88	1.62	1.85	.36
	Time management	2.92	2.23	2.15	2.21	.06
	Help seeking	2.92	3.05	2.92	3.07	.67
VRTMQ		2.82	2.68	2.69	2.55	.07
	Time planning	2,72	2,41	2,38	2,25	.12

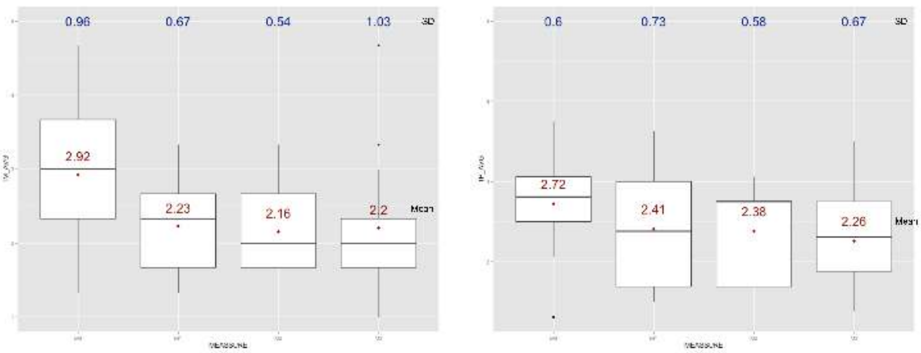
The results concluded in non-significant variances in the means justified by the low rate of participation in all the four measures. Hence, subscales with significance value lower or close to 0.1 were further examined. Based on this assumption, these results determine that the experimental manipulation has had some effect in "time management" and “time planning” subscales. This implies that one or more of the differences between mean is statistically significant. It is, therefore, necessary to carry out further analysis to find out which measure differ. As our specific hypothesis is that there will increasing “time management” (TM) and “time planning” (TP) skills as the experiment progresses, a set of planned contrast analysis were performed to determine whether our assumptions are true for the following sub-hypothesis:

- Hypothesis 1a: The first measure (M0) of the dependent variables “time management” and “time planning” is significantly lower than the subsequent measures.
- Hypothesis 1b: The first intermediate measure (M1) of the dependent variables is significantly lower than the subsequent measures.
- Hypothesis 1c: The second intermediate measure (M2) of the dependent variables is significantly lower than the last measure.

Table 3. Planned contrast for time management subscale (n=52). * Significance: $p < .05$

Planned contrast	**Contrast 1 Hypothesis 1a**		**Contrast 2 Hypothesis 1b**		**Contrast 3 Hypothesis 1c**	
	TM	**TP**	**TM**	**TP**	**TM**	**TP**
M0	X	X	-		-	
M1	(t=-2.14, p=.03)*	(t=-1.23, p=.22)	X	X	-	
M2	(t=-2.37, p=.02)*	(t=-1.34, p=.18)	(t=-0.2, p=.81)	(t=-0.1, p=.91)	X	X
M3	(t=-2.22, p=.03)*	(t=-1.83, p=.07)	(t=-0.08, p=.93)	(t=-0.5, p=.56)	(t=.15, p=.88)	(t=-0.5, p=.61)

The results of the first contrast determine that all measures taken during the course concluded in significant improvements in TM with respect to the initial measure at the kick-off of the course. Regarding the measure of TP, there was no significant variances and there might be only an improvement from the initial measure to the last one (p=.07). The results of the second and third contrast do not conclude significant variance between the intermediate measures of TM nor TP during the course. Overall these results substantiate the trends illustrated by the means in Figure 8ab. TM means in Figure 8a) depict an increase in this skill from the first measure (M0, Mean=2.92, SD=.96) to the second one (M1, Mean=2.23, SD=.67). This positive effect is again notable in the subsequent measure (M2, Mean=2.16, SD=.54). However, the last measure concluded with a slight decrease in TM skills (M3, Mean=2.2, SD=1.03). Means in Figure 8b) depict an increase in TP from the first measure (M0, Mean=2.72, SD=.6) to the next one (M1, Mean=2.41, SD=.73). Later on, the measure of TP slightly improves in the subsequent measures (M2, Mean=2.38, SD=.58; M3, Mean=2.26, SD=.67).



a) Time management b) Time planning

Fig. 8. Boxplot with mean scores (red dot/value) for significant subscales. X axis: measures M0 to M3; Y axis: reports 5) Strongly disagree; 4) Disagree; 3) Neutral; 2) Agree; 1) Strongly agree;

3.2 Impact of the timing in the notifications in self-regulated learning

The data obtained in the course C1 is used to evaluate this research question. Measures M0, M2 and M3 (n=39) are taken to contrast differences in TP and TM when varying the independent variable "timing" with scheduled-based notifications and random-based notifications. As our specific hypothesis is that students will improve "time management" (TM) and "time planning" (TP) skills when they receive notifications in schedule basis rather than when they receive notifications in random basis, a set of planned contrast is performed to determine whether our assumptions are true for the following hypothesis:

- Hypothesis 2: The intermediate measure M2 is significantly higher than the final measure M3, in contrast to the initial measure in M0.

Table 4. Planned contrast for time management subscale (n=39). * Significance: p < .05

Planned contrast	Contrast 1		Contrast 2	
	TM	TP	TM	TP
M0	X	X	X	X
M2	**(t=--2.52, p=.01)***	(t=-1.47, p=.15)	-	-
M3	-	-	(t=-2.52, p=.07)	(t=-1.86, p=.07)

The differences in the contrasts (Table 4) confirm significant differences in the variances from the initial measure M0 to M2 in TM (p=.01). Nevertheless, the variances in TM and TP are not significant in M3 in contrast to M0 (p=.07 in both TM and TP). Figure 8a illustrates that the differences in the mean contrasts to the initial measure M0 are slightly higher in M2 (M0-M2=.76) than in M3 (M0-M3=.72), and consequently consistent with our hypothesis.

Patterns sampling study time.

Distribution of time-logs along the day.
Time-logs registered during the courses C1, C2 and C3 are analysed to evaluate this research question. Students were able to log their study-time at any moment of the day along the week. As our specific hypothesis (H4) is the existence of patterns describing the way in which students study and log their time, our assumptions are true whenever we are able to find and understand these patterns.
Based on the results illustrated in Figure 9, there are three levels of intensity in the activity with regard to the number of time-logs performed:

- High Intensity (HI >80): Time ranges between 9h to 15h and 18h to 22h.
- Medium Intensity (20 < MI > 80): Time ranges between 8h to 9h, 15h to 18h and 22h to 0h.
- Low Intensity (LI < 20): Time ranges between 0h and 8h.

Regarding the average duration in the time-logs, students reported to study in longer time slots at 20h (100 minutes), 12h and 22h (80 minutes).

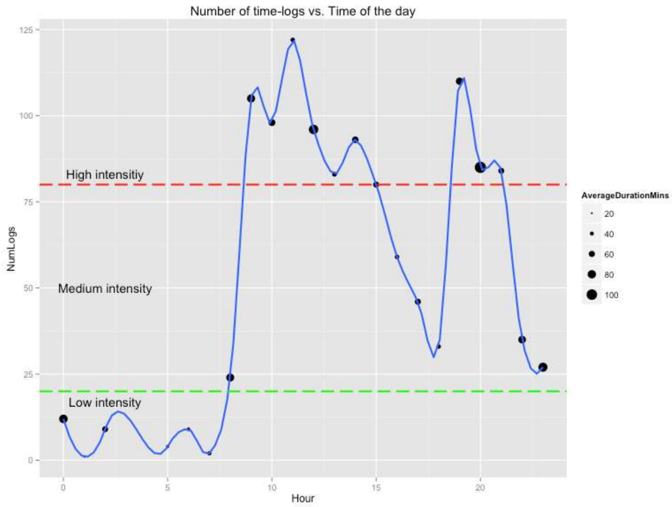


Fig. 9. Distribution of time-logs along the day (n=1456). X-axis: hour of the day. Y-axis: number of time-logs. The width of the plot (AverageDurationMins) represents the mean duration of the time-logs started in that hour.

Hereby, we explore how variations in timing of the notification moderate the number and the duration of the time-logs. Time-logs registered during the courses C1 are analysed to evaluate this research question (time-logs C2 and C3 are not included in this analysis for not being comparable to C1). As our specific hypothesis is that notifications will foster participants towards studying and consequently recording their time in the moment they receive the notification, our assumptions are true whenever there is an increase number (and duration) of time-logs recorded immediately after the notification. Figure 10 illustrates the time-logs recorded for the weeks in which the notifications were broadcasted at 20h. Figure 11 illustrates the time-logs recorded for the weeks in which the notifications were broadcasted at 10h. Figure 12 illustrates the time-logs recorded for the weeks in which the notifications were broadcasted at scattered moments in the day.

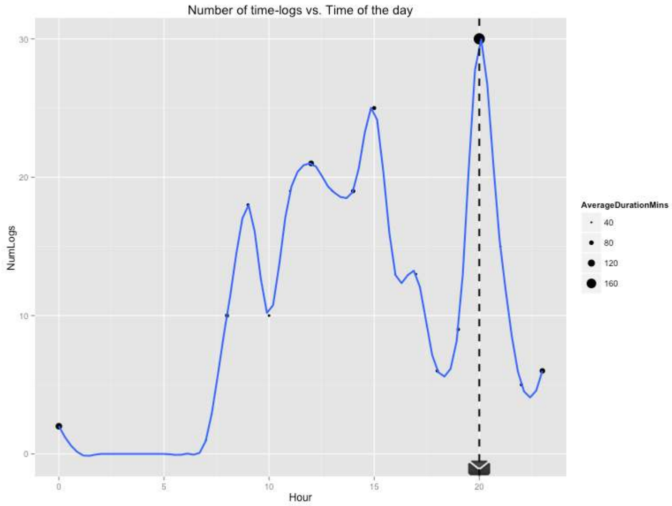


Fig. 10. Distribution of time-logs along the day (n=241) when SMS were prompted at 8pm. X-axis: hour of the day. Y-axis: number of time-logs. The width of the plot represents the mean duration of the time-logs started in that hour (AverageDurationMins).

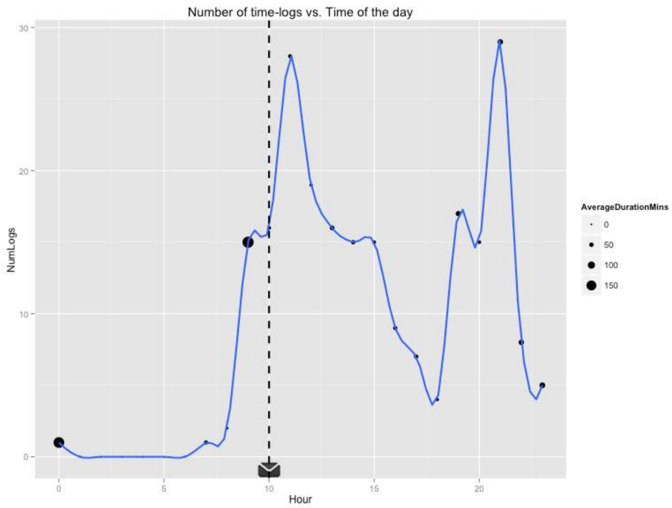


Fig. 11. Distribution of time-logs along the day (n=222) when SMS were prompted at 10am. X-axis: hour of the day. Y-axis: number of time-logs. The width of the plot represents the mean duration of the time-logs started in that hour (AverageDurationMins).

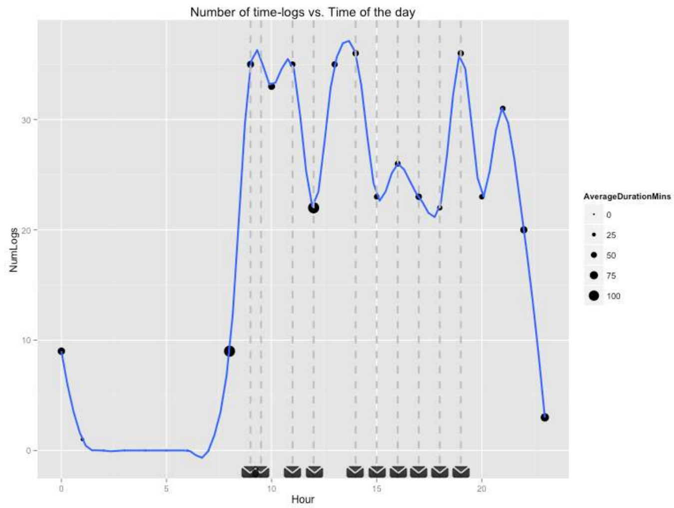


Fig. 12. Distribution of time-logs along the day (n=422) when SMS were prompted on random time basis. X-axis: hour of the day. Y-axis: number of time-logs. The width of the plot represents the mean duration of the time-logs started in that hour (AverageDurationMins).

Preferred timing

The last measure (M3) of the course C1 (n=13; α<70) included a question so students could rate their preference with regard to the timing when the notifications were delivered (5-Likert scale: 5.Most preferred; 3.Neutral; 1.Least preferred). Students preferred notifications prompted in the morning at 10h (M=3.77; SD=0.83) to notifications prompted in the evening at 20h (M=2.92; SD=1.03) and notifications randomly prompted throughout the day (M=2.85;SD=0.80).

Distribution of time-logs along the week.

As illustrated in Table 5, average time-logs per day fluctuate between 58 minutes to 83 minutes along the week. Students reported more minutes and more time-logs on Thursdays and Sunday. Longer time-logs were reported on Tuesdays and Wednesdays whereas the shorter ones are reported Mondays and Fridays.

Table 5. Distribution of time-logs along the week (1030)

Day of the week	%Time-logs(n)	% Minutes logged(n)	Mean duration of time logs in minutes
Monday	12.00% (n=146)	10.56% (n=8499)	58.21
Tuesday	12.16% (n=148)	15.39% (n=12387)	83.69
Wednesday	12.90% (n=157)	14.80% (n=11913)	75.87

Thursday	20.95% (n=255)	18.56% (n=14937)	58.57
Friday	11.34% (n=138)	10.69% (n=8603)	62.34
Saturday	12.08% (n=147)	11.75% (n=9457)	64.33
Sunday	18.57% (n=226)	18.25% (n=14692)	65.00

How do students log their time.

Students using the LearnTracker app were able to decide between recording their time in-action (Figure 3bc: clicking play when they start studying and clicking stop when they finish) or on-action (Figure 3b: clicking fast-forward when finished studying). Students using the Multiplatform web-interface could only record time their on-action. The records from the LearnTracker app are taken as indicator to identify preferences in the way to record time. 58.43% (n=534) of the recordings were performed synchronously in-action whereas the 41.57% (n=380) record their time asynchronously on-action.

Correlation between time-logging and performance.

The data obtained from the 29 students initially enrolled to the course C1 is used to evaluate this research question. Time-logs recorded during the course (n=1030) and the grades obtained in the final evaluation are taken as indicator. A Pearson's correlation analysis was performed with the aim to measure the strength in the relation between the grades obtained by the students and their time-logs along the course. The correlation of analysis between the grades and the number of time logs concluded in .37 (p=.20), whereas the correlation analysis between the grades and the total time recorded concluded in .09 (p=.76). Mean grades were calculated with the aim to identify differences between participants in the experiment (answered to M0 to M3) and not participants. Students not participating in the four measures of the experiment obtained slightly higher scores (n=13; M=6.53; SD=2.36) than the participants in the experiment (n=13; M=6.46; 1.66). There were three students more that did not attend to the final exam.

3.3 Impact from the content of the notifications in self-regulated learning

Hereby, we explore how variations in the content of the notification moderate the number and the duration of the time-logs. The data obtained in the course C1 is used to evaluate this research question.

Measures M0, M1 and M2 (n=39) are taken to contrast differences in TP and TM when varying the independent variable “content” with generic tips for self regulation and learning analytics. As our specific hypothesis is that students will improve “time management” (TM) and “time planning” (TP) skills when they receive learning analytics rather than tips, a set of planned contrast is performed to determine whether our assumptions are true for the following hypothesis:

- Hypothesis 3: The intermediate measure M2 has higher significance in contrast to the initial measure M0, than the intermediate measure M1 in contrast to the initial measure in M0.

Table 6. Planned contrast for time management subscale (n=39). * Significance: $p < .05$

Planned contrast	**Contrast 1**		**Contrast 2**	
	TM	TP	TM	TP
M0	X	X	X	X
M1	**(t=-2.14, p=.04)***	(t=-1.19, p=.24)	-	-
M2	-	-	**(t=-2.52, p=.01)***	(t=-0.47, p=.15)

The differences in the contrasts (Table 6) for TM confirm significant variances in M2 (p=.01) and M1 (p=.04). The differences in the contrasts do not confirm significant variances for TP. Figure 8a shows that the differences in the mean contrasts to the initial measure M0 are slightly higher in M2 (M0-M2=.34) than in M1 (M0-M1=.31), and consequently consistent with our hypothesis.

Preference in content and channels.

The intermediate measures M2 and M3 included three items so students could rate their preference with regard to the content of the signals and the channels use in a 5-Likert scale (5.Most preferred; 3.Neutral; 1.Least preferred). These results should be interpreted carefully justified by the low number of reports (n=13) and the scores obtained in the internal consistency tests (Cronbach’s reliability acceptance α >=70).

The second measure (M2) of the course C1 included a question so students could rate their preference with regard to the content of the notifications (See Appendix B). Students preferred learning analytics

(M=2.84; SD=0.69) to generic tips on self-regulation (M=2.54; SD=0.77) confirming our assumptions (α<70).

The last measure (M3) of the course C1 included a question so students could rate their preference with regard to the channel to receive learning analytics at their mobile devices. Students preferred on-demand graphics and chart visualizations (M=3.46; 1.13) to pushed SMS notifications (M=3.31; SD=0.5) confirming our assumptions (α<70).

Additionally, the last measure (M3) of the course C1 included a question so students could rate their preference with regard to the specific content of the learning analytics. Our assumption is that students will appreciate teacher's expertise and consequently find their estimations more useful than learning analytics reporting on the time devoted by their colleagues or individually by the student. Contrary to our hypothesis (α>70), students preferred personal learning analytics (Mean=3.69; SD=0.85) to social analytics (Mean=3.46; SD=0.88), and teacher´s estimations (Mean=3.38; SD=0.96).

3.4 Usability of the tool

The data obtained in the course C1 is used to evaluate hypothesis 5. Both the LearnTracker and the multiplatform web interface were presented and demoed at the kick-off as mobile tools to record their study-time. Participants were invited to voluntarily use the tool that better fit their preferences and the features of their mobile devices. Table 7 enumerates the list of actions (clicks, swipes or scrolls) needed to log study-time in both tools contrasting the best-case scenario (minimizing the number of interactions selecting first activity in the yardstick, minimizing scrolling selecting HH:MM, etc) with the worst-case scenario (scrolling to select bottom activity in the yardstick, maximum number of HH:MM in the scroll lists). The results show that the LearnTracker for Android requires 4 to 8 eight clicks to log time whereas the Multiplatform web interface requires 8 to 12 clicks.

Table 7. Summary of interactions to accomplish a time-log. (* Number of actions / Number of clicks)

LearnTracker for Android		**Multiplatform web-interface**	
Minimum	**Maximum**	**Minimum**	**Maximum**
1 click to start app	1 click to start app	1 click URL on SMS	1 click URL on SMS
1 click select 1st activity	2 clicks to scroll and select bottom activity	1 click to display HH scroll 1st activity	2 clicks to scroll and select bottom activity
1 click to check-in	2 scroll bottom HH	1 click to select HH	1 click to display HH scroll
1 click to check-out	2 scroll bottom MM	1 click on “done”	2 clicks to scroll and select bottom HH
	1 click fast-fwd asynch. log	1 click to display MM scroll 1st activity	1 click on “done”
		1 click to select MM	1 click to display MM scroll
		1 click on “done”	2 clicks to scroll and select bottom MM
		1 click on “send”	1 click on “done”
			1 click on “send”
4/4	**5/8**	**8/8**	**9/12**

After demoing the tools at the kick-off, students become aware of the differences in the complexity of the interactions in number of clicks, as well as of the differences between fast swiping screens within the app, web browser navigation from one page to another. Another relevant difference is that the multiplatform web interface only presents the learning analytics (Figure 5bc) just after logging time whereas the LearnTracker facilitates monitoring of the visualizations at any moment accessing from the yardstick screen (Figure 3a). Hence, some of the non-Android students (i.e. iOS, Windows, Blackberry) expressed to be dissatisfied with the difference in the tooling and did not accept take part in the experiment. These differences were also obvious during the course, when the majority of the Android students completed the whole course logging their study-time in contrast to the multiplatform web interface.

Finally 11 students decided to use LearnTracker while 6 students selected the mobile web interface. The System Usability Scale (SUS) was used for the evaluation of the usability [32]. The SUS scale consists of 10 questions with a five-point Likert scale, where item directions are changed in each question. The results of the survey were recorded in an online questionnaire. Based on the current literature, a SUS score above 68 (SD: 12.5) is rated as usability score above average. This analysis have followed the recommendations from Sauro [33] so that the results can be mapped and benchmarked against 446 previous studies and 5000 individual responses. The evaluation of the usability shows that LearnTracker for Android has a mean score of 76.8 (SD = 8.4), which is remarkably above average. Items 4 and 10 from the questionnaire were taken as subscale for learnability. Average learnability score was 72.7. Items 1, 2, 3, 5, 6, 7, 8, 9 contribute to the construct usability where average score was 93.2. On the other hand, the evaluation of the usability shows that multiplatform web interface has a mean score of 55.0 (SD = 12.6), which is below average. Values for learnability and usability were 95.8 and 44.8 respectively.

4 Discussion

4.1 Interpretation of the results

This manuscript has explored the use of mobile time-logs to foster self-regulated learning in online environments. Learning analytics delivered to students via mobile chart-visualizations and notifications have been used with the aim to support them in the competence development of "learning to learn" [9] by raising awareness on *time management* as trigger to foster understanding on meta-learning [13], [36]. The analysis of the results concludes in the following findings:

Benefits of logging study-time

Findings in this study suggest that using mobile devices to log and track the time devoted to study across contexts might lead to an improvement on *time management skills*. This subscale of self-regulated learning [28] comprises items assessing whether students allocate extra study-time for online courses, whether students observe the schedule setting aside the same time everyday or every week to study on online courses, and last but not least, whether students even without having the obligation to attend daily classes, still try to distribute study time evenly across days. The results presented in Table 3 and illustrated in Figure 8a show increased values in the skill of time management from the first measure (M0) to the third one (M2), remaining stable in the subsequent measure. Additionally, the results show that there might be a significant positive effect in the measure of *time planning* (Figure 8b). This subscale [31] comprises more generic items (beyond online courses) that asses whether students set learning goals, write goals, set priorities, plan ahead the week, etc. These results show that logging and monitoring time can foster time management skills in online courses with increased values from the initial start to the 10^{th} week when the values remain stable. In further research, studies in longer courses (than 4 months) should explore whether this measure remains stable or fluctuates after that time.

Timing of mobile notifications

Findings in the experiment suggest that notifications pushed at random time of the day do not produce significant improvements in time management. Nevertheless, notifications pushed at fixed times of the day might moderate positively the measure of time management. These results are consistent with the answers reported by the students regarding their timing preference, in which, notifications at 10h were preferred over notifications at 20h, and over notifications randomized in time. More investigation is needed into the tension of intruding students' “out-of-school” time with notifications. Another reason to argue on these results might be that students prefer notifications that persuade them to (pre-)“plan ahead” their learning day, rather than (post-)“look backward” their learning day or (in-action) “plan” at any moment of the day.

Benefits of mobile notifications containing learning analytics

Findings in the experiment suggest that notifications containing learning analytics and generic tips on self-regulation might influence positively the skill of time management. More specifically, notifications containing learning analytics resulted in slightly higher scores in time management, in comparison to generic tips on self-regulation (See Appendix B). These results are also consistent with the answers reported by the students regarding their content preference, in which, students preferred learning analytics over tips. The results indicate that students perceive learning analytics informing about their personal time-performance and behaviour more useful, in comparison to learning analytics informing about the progress from peer learners or time per task estimated from the teacher. Students preferred chart visualizations over text messages to receive learning analytics. Nevertheless, the preference for this channel does not imply that visualizations are more effective. SMS notifications get the primary attention of the students suggesting learning cues in the moment they are pushed to their mobile devices (foreground), whereas chart visualizations are always running in the mobile device and might stay in the background unless there is an intrinsic interest from the students to visualize them and obtain conclusions out of them.

The authors of this research want to further research the effects of SMS to foster self-regulated learning. Indeed, occasional “stop and think” beacons containing adequately contextualized messages can support students in the competence of learning to learn in online courses, specially when they are combined with suitable visualizations. Taking actions to dismantle barriers for lifelong learners (i.e. lack of personalisation (B1), time and place constrains (B2), the lack of facilities to study at home (B3), fragmentation in learning experiences (B4) [1]) providing mobile and contextualized learning requires finding the suitable balance between prompting mobile learning analytics via chart visualizations and via notifications so none of the channels falls into a disregard background in which the signals are definitely ignored. Tabuenca et al. [13] stressed the importance in the timing and content of the notifications to foster reflective practice on meta-learning suggesting sporadic notifications with specific instructions. In this experiment, we have extended their research prompting two notifications per week. Notifications in this study (i.e. See Appendix B. LA-09 “*Hi Natalia, your colleagues report 53% of their study-time between 19h and 22h*”.) were customized to the user receiving the notification but also providing real time feedback on the behaviour of the colleagues. We suggest featuring notification that are even more contextualised (e.g. LA-09 notification was not prompted in the time range between 19h and 22h). Further research is needed to explore whether these notifications trigger reflection episodes leading to better learning performances when the content is directly bound to the personal context of the student in the same moment (and/or location) when (where) the notifications are dispatched.

Patterns logging study-time on mobile devices

Findings in this experiment confirm the existence of specific patterns in the way students use personal mobile devices to sample their study-time.

- Daily patterns. The number and the duration of the time-logs presented in Figure 9 show that there are two specific time-ranges of the day (09h-15h and 18h-22h) when students are more active.
- Weekly patterns. Thursdays (18.56%) and Sundays (18.25%) were the days with more activity in contrast to Mondays (10.56%) and Fridays (10.69%) balancing the over-performance from the previous day in a “rebound effect”.
- Effects of notifications. Figure 10 shows that there is a clear increase in the number of time-logs just after the signal when notifications were delivered at 20h. Not less remarkable is the effect when the notifications were delivered at 10h (Figure 11) peaking up again just after the delivery time. Additionally, Figure 11 shows that the activity just after 20h has remained peaking up probably caused by the continued effect from the previous treatment. The relation cause-effect between notifications and time-logs is again visible in Figure 12. In this case, the notifications were broadcasted along the day (see dashed lines) producing more constant number of time-logs (less fluctuations) along the day in contrast to Figure 10 and Figure 11. Hence, we conclude that this effect was persistent during the whole time study.
- Recording mode patterns. There were more students that preferred to log their time in-action using the synchronous mode of the app (58.43% of the time-logs. n=534) rather than post-logging with the asynchronous mode (41.57% of the time-logs. n=380). This preference is probably caused by the fact that synchronous mode ensures more accurate time-logs.
- Performance correlation between grades and samples. The results from this experiment show that there seems to be no correlation between the number of time-logs (nor the duration) and the grades obtained in the evaluation at the end of the course. This confirms that time-logging is not an activity for a limited group of students (for example high-achievers) but seems to be useful for all students. Likewise, the simple fact of participating in the experiment

did not lead to substantial differences in grades with respect to students that did not participate.

Usability in mobile tools for time logging

Based on the measures from the students that participated using the tools to record their study-time for a minimum of 2 months, we have described the importance of providing simple and usable interfaces to integrate mobile support activities in daily routines.

The measures of complexity reported in Table 7 evidence the differences in the complexity of the tooling. Hence students had different way to report depending on the logging tool they were using. Moreover, the granularity of the time logs in LearnTracker was smaller than in the web-based platform. Students using LearnTracker could only log time for one assignment in one transaction, whereas students using the web-interface could log time from multiple assignments in the same transaction. Indeed, the observation of the reports show that students using this tool, usually reported time-logs for multiple assignments in one transaction. Hence, students using the web-interface were less constant reporting time, affecting to the quality of their learning analytics, losing engagement with the tool, and consequently leading to a higher rate of dropouts.

Based on the observations, the measures of complexity, and the results from the usability test suggest, we conclude that LearnTracker for Android is a suitable interface to log study-time in online environments in comparison to the web-interface tool.

4.2 Limitations

Most of the conclusions presented in this manuscript are based on the data reported by 13 students taking part in an online university course (C1) for 4 months. Hence, there is a need to provide consistency to these findings extending the research questions to larger groups.

In H1, we explored the relationship between logging and monitoring study-time, and self-regulated learning for which positive effects on time management skills were discussed. Nonetheless, this improvement might be moderated by the simple fact of starting the activity within the course. In further research, the variables analysed in this study (i.e. timing, content, tool) should be isolated and contrasted in separated control and treatment groups.

In H2 and H3, we explored the impact of notifications (i.e. timing and content) in self-regulated learning. Some of the effects identified in the intermediate measures might be moderated as a consequence of sequencing effects, and not only caused by the treatment delivered during each concrete treatment. More research is needed evaluating these treatments to separated groups, but also contrasting the results with a control group that would not record nor monitor time using their mobile device.

The design of this experiment has comprised repeated measures in short periods of time (i.e. every 4 weeks in C1, every 3 weeks in C2 and C3). On the one hand, testing effects might have moderated their reports due to the short time between measures. On the other hand, some of the participants could not complete the intermediate measures on time, and consequently their data could not be taken into the analysis. In further research, we suggest performing only one treatment per group in single pre and post questionnaires for periods longer than 4 weeks.

The results and patterns described in this experiment are based on the reports from students using two different mobile tools (i.e. LearnTracker and web-based platform) that might be leading to differences in TM and TP (hypothesis 1, 2 and 3). The results cannot be analysed separately justified by the low participation. In further research, this variable should be isolated so the results are concluded from students using the same tool.

4.3 Significance of the study and implications for practice

The contribution of this study is fourfold: first, providing empirical results on the effects of sampling study-time using personal mobile devices and providing real time learning analytics from two different channels, namely, notifications and visualizations; second, releasing an open source working platform to facilitate further research on the effects of providing feedback on time devoted to learning in online courses; third, describing specifications and “know how” instructional designers and teacher could implement similar approaches; forth, highlight intriguing research questions for further research in the use of mobile notifications to foster self-regulated learning.

In future work, we will use mobile time-logs to evaluate how accurate are the time estimations from teachers, how much fluctuates the number and duration of time-logs among students, and whether these time-logs can be used to identify potential dropouts in a course. Additionally, we will extend the framework providing open source tools for iOS and web interfaces to facilitate access to all students.

Appendix A

List of available commands in LearnTracker's Backend API:

Table	**Command**	**HTTP Method**	**Description**
Subject	getSubject	GET	Returns subject for a given identifier
	insertSubject	POST	Inserts subject entered as parameter into database
	listSubject	GET	Lists all existing subjects.
	listSubjectCourse	GET	Lists subjects configured for a given course [See example*1]
	removeSubject	DELETE	Removes subject with given identifier
	updateSubject	PUT	Updates subject with given identifier with the values given as parameter
User	getUser	GET	Returns user for a given identifier
	insertUser	POST	Inserts user entered as parameter into database
	listUser	GET	List all users
	listUserCourse	GET	List users enrolled in a course (subject) [See example *2]
	removeUser	DELETE	Removes user with a given identifier
	updateUser	PUT	Updates user with given identifier with the values given as a parameter
Activity	getActivity	GET	Returns activity for a given identifier
	insertActivity	POST	Inserts activity entered as parameter into database
	listActivity	GET	Lists all existing activities
	listActivityCourse	GET	List all the activities for a specified course (subject)
	listActivityCourseUser	GET	List activity for a given user enrolled in a course [See example *3]
	removeActivity	DELETE	Removes activity for a given identifier
	removeActivityCheckI-nUser	DELETE	Removes check-in activity for a given users
	updateActivity	PUT	Updates activity with given identifier with the values give as parameter

Examples:
[*1] List assignments defined in the yardstick of the Geographical Information Systems course with id "N35231":
https://lifelong-learning-hub.appspot.com/_ah/api/subjectendpoint/v1/subject/course/N35231

[*2] List students enrolled in the Geographical Information Systems course with id "N35231":
https://lifelong-learning-hub.appspot.com/_ah/api/userendpoint/v1/user/course/N35231

[*3] List activity (time-logs) recorded by the student with name "Mark" during the course with id "S23222":
https://lifelong-learning-hub.appspot.com/_ah/api/activityendpoint/v1/activity/course/S23222/user/Mark

Appendix B

List of mobile notifications broadcasted to students during the course:

Generic tips for self-regulation

Tip 01: Hi {First name}, plan ahead! Schedule it and it will happen! Determine how long your tasks will take before starting. Record your time via {URL mobile tool}

Tip 02: Hi {First name}, use "to do" lists for both long-term and for each day/week. Record your time via {URL mobile tool}

Tip 03: Hi {First name}, plan to spend at least 50 per cent of your time engaged in the activities that produce most of your results. Record your time via {URL mobile tool}

Tip 04: Hi {First name}, practice not answering e-mails just because they show up. Disconnect instant messaging while studying. Record your time via {URL mobile tool}

Tip 05: Hi {First name}, know your deadlines! Mark the deadlines out clearly in your calendar so you know when you need to finish them. Record your time via {URL mobile tool}

Tip 06: Hi {First name}, focus! Are you multi-tasking so much that you're just not getting anything done? If so, focus on just one key task at one time. Record your time via {URL mobile tool}

Tip 07: Hi {First name}, end your working day at a fixed time. Don't let work creep to fill your entire evening. Record your time via {URL mobile tool}

Tip 08: Hi {First name}, do a time audit for one week and look at exactly where your time is going. Notice where you spend your time on a regular weekday. Record your time via {URL mobile tool}

Tip 09: Hi {First name}, be proud of your learning time. Account all the time you need to study. Record your time via {URL mobile tool}

Tip 10: Hi {First name}, Study at a pace where you can attend to each matter and task effectively. Keep recording your time via {URL mobile tool}

Tip 11: Hi {First name}, Plan ahead and don't forget to schedule in time to relax and breathe. Record your time via {URL mobile tool}

Tip 12: Hi {First name}, plan for the unexpected. Expect the unexpected so you don't have to spend more unplanned time trying to fix your mistakes. Record your time via {URL mobile tool}

Tip 13: Hi {First name}, schedule rewards!. Schedule a fun afternoon, your brain will need it. Record your time via {URL mobile tool}

Tip 14: Hi {First name}, find your productive time!. Are you a morning person or a night person? You'll be more efficient if you work when you're at your best.]. Record your time via {URL mobile tool}

Tip 15: Hi {First name}, organize your study area before starting to study. Make sure you have all of the supplies you need. Record your time via {URL mobile tool}

Tip 16: Hi {First name}, keep your work with you. That way, if you find yourself with extra time while on the train or bus or waiting for an appointment you can get something done. Record your time via {URL mobile tool}

Learning Analytics

LA 01: Hi {First name}, you and your colleagues record an average of 1 hour 21 minutes every time they study Klinische I. Please record your learning time via {URL mobile tool}

LA 02: Hi {First name}, you and your colleagues record an average of 7 hours 9 minutes studying Klinische I by week. Please record your learning time via {URL mobile tool}

LA 03: Hi {First name}, you and your colleagues devote 4 hours 51 mins less than foreseen by the teacher on average to study Klinische I by week. Please record your learning time via {URL mobile tool}.

LA 04: Hi {First name}, so far "Biologische benaderingen van psychopathologie" is the chapter were students reported to invest more time. Please record your learning time via {URL mobile tool}.

LA 05: Hi {First name}, Time devoted to study "Algemene inleiding en het terrein van de klinische psychologie" has fluctuated from 4 hours to 13 hours. Please record your learning time via {URL mobile tool}.

LA 06: Hi {First name}, "Hfdst 7 en hfdst 8" are the chapters in which you and your colleagues reported to invest less time so far. Please record your learning time via {URL mobile tool}.

LA 07: Hi {First name}, "Hfdst 2" is the chapter in which you and your colleagues reported to invest less time so far. Please record your learning time via {URL mobile tool}.

LA 08: Hi {First name}, Mondays & Wednesdays are the preferred days to learn Klinische. 9am and 1pm are the preferred times of the day. Please record your learning time via {URL mobile tool}

LA 09: Hi {First name}, between 9am and 11am is the most preferred moment to study Klinische I. Record your time via {URL mobile tool}

LA 10: Hi {First name}, between 5pm and 7pm is the least preferred moment to study Klinische I. Record your time via {URL mobile tool}

LA 11: Hi {First name}, Sunday and Thursday are the preferred days to learn Klinische I with 30% of the recordings. Record your time via {URL mobile tool}

LA 12: Hi {First name}, Friday is the least preferred day to learn Klinische I with only 7% of the recordings. Record your time via {URL mobile tool}

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