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

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A B S T R A C T

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.

1. Introduction

One of the main challenges in the field of Technology Enhanced Learning is the recognition of the activities and contexts of learners (Kalz, 2014). 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 (Hachey, Wladis, & Conway, 2015), describing (Hung & Zhang, 2008; Wresch, Arbaugh, & Rebstock, 2005; Yang, Li, Guo, & Li, 2015), or providing suitable guidance on patterns of behaviour to support the learning process in online learning environments (e.g. in Learning Management Systems (Brusilovsky & Henze, 2007) or in MOOCs (Gillani & Eynon, 2014)), little is known on how students devote their time to learn across contexts beyond the boundaries of the virtual platform.

Longworth (Longworth, 2013) 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

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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 (Kalz, 2014) 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 (European Commission, 2007). 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 (Winne, 2001; Zimmerman, 1990). 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 (Kalz, 2014):

1.1.1. Psychology of notifications

Recent work shows that simple notifications via SMS are useful to promote self-regulation (Goh, Seet, & Chen, 2012) and reflective practice on meta-learning (Tabuenca, Kalz, Ternier, & Specht, 2015). Tabuenca et al. (Tabuenca, Kalz, Börner, Ternier, & Specht, 2014) 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 (Hektner, Schmidt, & Csikszentmihalyi, 2007)) 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 (Tabuenca et al., 2015a) 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 (Tabuenca et al., 2014a)) 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 (Tabuenca et al., 2014a)). 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.

1.1.2. Learning analytics

Learning analytics are driven by the collection and analysis of traces that learners leave behind (Greller & Drachsler, 2012). It can help to understand and optimise the learning process and the environments in which it occurs (Siemens & Long, 2011). Until now, learning analytics are mostly feedback to the users in web-based learning dashboards (Verbert et al., 2014). 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” (Candy & Brookfield, 1991). 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 (Fulantelli, Taibi, & Arrigo, 2013), (Aljohani & Davis, 2012). 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