Computers & Education 96 (2016) 42–54

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Students' LMS interaction patterns and their relationship with achievement: A case study in higher education

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A R T I C L E I N F O

Article history:
Received 18 March 2015
Received in revised form 5 February 2016
Accepted 17 February 2016
Available online 21 February 2016

Keywords:
Learning management systems
Interactive learning environment
Postsecondary education
Interaction patterns

A B S T R A C T

The use of Learning Management Systems has grown exponentially in the last several years and has come to have a strong effect on the teaching-learning process, particularly in higher education. The present study intends to examine students' asynchronous learning processes via an Educational Data Mining approach using data extracted from the Moodle logs of students who were grouped according to similar behaviors regarding effort, time spent working, and procrastination. The behaviors were then matched with different levels of achievement.

First, the different patterns of students' involvement in the learning process in a Learning Management System were clustered. Second, the different variables selected from the Moodle records were studied to see if they were equally suitable for the configuration of student clusters. Third, the relationships between those patterns to students' final marks were examined.

After analyzing the log data gathered from a Moodle 2.0 course in which 140 undergraduate students were enrolled, four different patterns of learning with different final marks were found. Additional results showed that there are variables more related to achievement and more suitable to group the students on the basis of which the different groups were characterized, namely, two *Task Oriented Groups (socially* or *individually focused)* and two *Non Task Oriented Groups (procrastinators* or *non-procrastinators)*. These results have implications in the design of interventions for improving students' learning processes and achievement in LMSs.

1. Introduction

The use of Learning Management Systems (LMS) has grown exponentially in the last several years, particularly in higher education (Romero, Espejo, Zafra, Romero, & Ventura, 2013). LMS have had and are currently having a strong effect on knowledge acquisition, and empirical research in cognitive science and computer science is addressing this subject from different perspectives (Azevedo & Aleven, 2013). The findings reveal, however, that not every student profits from the learning-assumed opportunities of LMS (Lust, Collazo, Elen, & Clarebout, 2012) and that learner control in using LMS tools cannot be taken for granted (Lust, Vandewaetere, Ceulemans, Elen, & Clarebout, 2011). There is abundant empirical evidence

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http://dx.doi.org/10.1016/j.compedu.2016.02.006

suggesting that learners do not successfully adapt their behavior to the demands of advanced learning environments, such as LMS (Azevedo & Feyzi-Behnagh, 2011). Learning in environments like LMS requires more effort by the student when deciding what, how, and how much to learn; how much time to invest; when to abandon and change learning strategies; when to increase effort; and so on. (Azevedo, Cromley, Winters, Moos, & Greene, 2005).

Furthermore, in traditional learning settings, instructors can easily gain insight into the way students work and learn. In LMS, however, it is more difficult for teachers to understand how the students behave and learn in the system (Graf & Liu, 2009), and compared to other systems that structure interactions, these environments provide data on the interaction at a very low level. Because learner activities are crucial for an effective online teaching-learning process, it is necessary to search for empirical methods to better observe patterns in the online environment (Neuhauser, 2002).

In addition, exploring how different patterns of student behavior in LMS are related to final achievement could be highly useful for the design of Adaptive Hypermedia Systems (AHS) or Adaptive Educational Systems (AES) (Brusilovsky, 1996; De Bra & Calvi, 1998). Traditionally, AHS adaptations were based on knowledge prerequisites, browsing data, or autobiographical information (age, gender, etc.), e.g., AHA (Bra & Calvi, 1998)! or My Online Teacher (Cristea & De Mooij, 2003; Cristea, Smits, & Bra, 2007); however, another approach to AHS has emerged that is based on students' interaction data with the system at a very low level of granularity (Romero, Ventura, & García, 2008; Romero, Ventura, Zafra, & Bra, 2009), similar to the aim of the present work. Currently, the goal of this approach is to polish and refine as much as possible the scaffolding that the system provides to every student. As previously noted by Dabbagh and Kitsantas in 2005 and 2013, scaffolding the acquisition of student SRL (Self-Regulated Learning) processes is particularly important in web-based courses because students are often asked to complete learning tasks with little or no support, requiring students to be highly self-regulated.

1.1. Educational data mining approach and students' behavior in LMS

The present work intends to shed light on students' interactions with LMS from an Educational Data Mining (EDM) approach that simultaneously underpins the adaptation of learning environments. Variables such as effort, working time, and procrastination are deduced from Moodle logs to help answer the following types of questions: Can students adapt to the demands of the current learning environments? Does their ability to adapt have any effect on their achievement? Going further, can we adapt those online environments to the students' characteristics? Do all learners really need an adaptation or only recommendations? These and other similar questions arise when reflecting on where we are headed in the field of computer-based learning environments and, furthermore, where are we trying to lead learners. In summary, it would be worthwhile to have in-depth knowledge of students' behavior in these environments and understand how this affects their performance, which in turn will contribute to the improvement of the learning process. For this purpose, EDM is one of the latest techniques that can help us better understand the interaction between the user and an information management system (Agosti, Crivellari, & Di Nunzio, 2012).

In recent years, researchers have investigated various data mining methods to help instructors and administrators improve e-learning systems (García, Romero, Ventura, & de Castro, 2006). EDM is focused on developing and applying computerized methods to detect patterns in large collections of educational data that would otherwise be difficult or even impossible to analyze (Romero, Ventura, Pechenizky, & Baker, 2010). EDM is also specifically applied to examine data in LMS, as explained by Romero, Ventura, and García (2008). In particular, EDM has already been used to predict dropouts and academic successes (Romero, Espejo, 2013), identify at risk students (Arnold & Pistilli, 2012; Essa & Ayad, 2012; Baker, Lindrum, Lindrum, & Perkowski, 2015; Macfadyen & Dawson, 2012), automatically track students' activities in LMS (Govaerts, Verbert, Duval, & Pardo, 2012; Leony, Pardo, de la Fuente Valentín, de Castro, & Kloos, 2012) and predict student achievement (Romero-Zaldivar, Pardo, Burgos & Kloos, 2012), among others.

As shown in the last review by Romero and Ventura (2010), a significant number of quality studies have been conducted with techniques similar to those used in the present work; many of them were carried out in laboratory settings over a short period of time and with decontextualized tasks in terms of real academic context.

The added value of the present work is that it is carried out in a real setting, going beyond laboratory contexts and even a researcher-controlled setting by using tasks belonging to the official student curriculum. Moreover, it expands the usual short period of time of these experiences, extending the implementation time to an entire semester. There are also some related studies approaching the issue outside of laboratory contexts.

1.2. Related work

1.2.1. Pattering students' behavior in LMS

In the last decades, a good number of studies have tried to pattern student's behavior in LMSs with different purpose, since identify learning styles (Graf & Liu, 2009; Özpolat & Akar, 2009) to predict students motivation (Dawson, Macfadyen, & Lockyer, 2009; Munoz-Organero, Muñoz-Merino, & Kloos, 2010). Go in depth, Murray, Pérez, Geist, and Hedrick (2012) have observed that the resources a student interacts with could contribute to making learning easier for students and increasing their learning progress. They analyze thresholds regarding variables related to effort, such as time spent on exercises, results, self-assessment tests, and discussion forums, but with the goal of automatically identifying learning styles. Lust, Elen, and Clarebout (2013a), observed how students differ in their tool-use within each learning phase of a course in a LMS clustering variables like time on web-lecture, time on web-link, time on feedback,