Computers in Human Behavior xxx (2016) 1–13

Contents lists available at ScienceDirect

Computers in Human Behavior

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

Validation of indicators for implementing an adaptive platform for MOOCs

Dolores Lerís [a], María Luisa Sein-Echaluce [a], Miguel Hernández [b], Concepción Bueno [c, *]

[a] Department of Applied Mathematics, University of Zaragoza, School of Engineering and Architecture, María de Luna 3, 50018 Zaragoza, Spain
[b] Computer Center, Catholic University of Valencia, Plaza San Agustín 3 Entresuelo B pta C, 46003 Valencia, Spain
[c] Department of Educational Sciences, University of Zaragoza, Faculty of Education, Pedro Cerbuna 12, 50009 Zaragoza, Spain

ARTICLE INFO

Article history:
Received 29 April 2016
Received in revised form
20 July 2016
Accepted 23 July 2016
Available online xxx

Keywords:
Personalized learning
Massive open online courses
Adaptive systems

ABSTRACT

Personalization techniques are a classic solution recommended by many experts for improving learning. Information and communication technologies and online courses have helped reduce the difficulties teachers face with a diversity of student profiles and a large number of students in a classroom. When these factors are extreme, like in a Massive Open Online Course (MOOC), those techniques may be the solution. However, even the most sophisticated technologies have not solved all the challenges posed by personalized learning, and in cases where teachers are not skilled in the technology they must use, the adaptive systems have only complicated the implementation of online courses. Therefore, this paper proposes a construct of adaptivity for MOOCs to identify some specific personalizing indicators. These indicators are chosen as a result of previous work done and are based on two aspects of learning: self-regulation and cooperation. This construct presents a consistent scale. A study is conducted to find the indicators that are most acceptable to participants in a MOOC, and it considers whether the performance or completion of other MOOCs previously influences the participant's perception of the value of the proposed construct.

1. Introduction

Massive Open Online Courses (MOOCs) are seen as the natural extension of the open courses created within movements such as OpenCourseWare (Fidalgo Blanco, Sein-Echaluce, Borrás Gené & García Peñalvo, 2014). MOOCs have their origins in an open online course created in 2008 by George Siemens and Stephen Downes as an introductory course to promote a master's course. That course had more than 2200 participants in addition to the master's students (Downes, 2008) and used an e-learning platform for its structured part, while the participants improved their knowledge and learning through Facebook, Second Life, blogs, wikis and other virtual spaces. The first MOOCs (called cMOOCs) were associated with a view of learning promoted by Siemens and Downes called Connectivism, a combination of network learning and the pedagogy of participation. Some years later, xMOOCs were developed, offered by traditional universities (Stanford (Coursera), MIT/Harvard (edX), Udacity, etc.) and based on their traditional online courses, with a focus on contents. There are multiple references to these two types of MOOCs and their combinations (Siemens, 2012; Ng & Widom, 2014; Cabero, Llorente & Vázquez, 2014; Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2015; Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2016).

The emergence of MOOCs with their specific typology and platforms has necessitated an evaluation of their achievements and the possibilities for their integration into traditional educational systems. The NMC Horizon Report of 2015 (Johnson, Adams Becker, Estrada & Freeman, 2015) includes MOOCs among the competing models of education as a 'wicked challenge', namely as being among 'Those that are complex to even define, much less address'. Many authors express opposing opinions regarding the value of MOOC training, whether as an opportunity for the dissemination of knowledge or in relation to its effects on preparation for the labour market (Raposo-Rivas, Martínez-Figueira & Sarmiento Campos, 2015; Zapata-Ros, 2013; Chiappe Laverde, Hine & Martínez Silva, 2015; Johnson et al., 2015). MOOCs are also considered tools for the dissemination of educational innovation and for the international visualization of educational institutions (Teixeira, Garcia-Cabot,

* Corresponding author.
E-mail addresses: dleris@unizar.es (D. Lerís), mlsein@unizar.es (M.L. Sein-Echaluce), miguel.hernandez@ucv.es (M. Hernández), cbueno@unizar.es (C. Bueno).

http://dx.doi.org/10.1016/j.chb.2016.07.054
0747-5632/

García-Lopéz, Mota, & de-Marcos, 2016). They can be used for the creation of subunits of participants who share the same language, geographic location or any other aspect in which they have affinity (Siemens, 2013). The literature about MOOCs has been greatly enriched in recent years by studies and general reflections (Daniel, 2012; Hollands & Tirthali, 2014; Liyanagunawardena, Adams, & Williams, 2013) and it has covered specific aspects such as the advantages and disadvantages of MOOCs (Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2015; García-Peñalvo, Fernández-Hermo, Fidalgo-Blanco & Sein-Echaluce, 2014; Zhang, 2016), the profiles and competences of the participants (Fidalgo-Blanco, Sein-Echaluce, García-Peñalvo & Esteban Escaño, 2014; García-Peñalvo, Cruz-Benito, Borrás-Gené & Fidalgo Blanco, 2015) or the impact of MOOCs on the e-learning (Martínez Abad, Rodríguez Conde & García-Peñalvo, 2014).

One of the variables by which the quality of MOOCs is defined is the dropout rate (Brahimi & Sarirete, 2015). Jordan (2014) defines the completion of a MOOC as being the percentage of participants who manage to meet the requirements for obtaining a certificate (MOOC completion rates range from 0.9% to 36.1%, with an average of 6.5%). Jordan also defines active participants in a course as those who have accessed the course, made an attempt to answer a questionnaire, or who have seen at least one video (54% of participants qualify as active, and when calculating the completion rate from active participants only, the rate goes up to between 1.4% and 50.1%, with an average of 9.8%).

Hill (2013) established a typology of participants in Coursera's MOOCs as No-shows, Observers, Drop-Ins, Passive participants and Active participants. Of these types, only the Active participants complete the whole course (with a very low rate, as mentioned) and this excludes the high rate of No-shows who do not even start the course. The rest of the participants do not do the evaluation activities or only search for specific contents according to their interests and then drop out after the second week of the course (Bernal González, 2015). These dropouts are the target of much research in order to find new ways of encouraging and motivating participants to complete a MOOC. The dropouts are understood to happen because MOOCs are traditionally designed in the same manner for every participant, without paying attention to the diversity of characteristics, learning objectives and motivations, which would require a personalization of learning (Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2015).

Personalized learning is not new in traditional teaching, but it has experienced a surge since the introduction of information and communications technologies because they have reduced the traditional barriers to personalized education (Edu-Trends, 2014). The technologies that support personalized learning are called Adaptive Learning Technologies (ALT) or Adaptive Systems, and Gartner (2015) has identified the top ten strategic technologies impacting education. The Horizon Reports of 2015 and 2016 (Johnson et al., 2015, 2016) identify the personalization of learning as being among the most significant challenges for the adoption of educational technology at universities. It is now identified as a 'Difficult Challenge: Those that we understand but for which solutions are elusive.'

ALT is not new, by the middle of the twentieth century Skinner's teaching machine was already working, following his theory of Programmed Learning, which was adapted to the learning pace of each student (Watters, 2015). Twenty years later, the appearance of Adaptive Hypermedia Systems (AHS) provided an alternative to the traditional 'one size fits all' approach, although the early systems were based solely on the adaptation of texts to users (Brusilovsky, 1996). Later, they started to focus on learning content and design (Carro-Salas, 2001; Berlanga & García-Peñalvo, 2005, 2008).

Most studies of online teaching have focused on MOOCs because they exhibit the most extreme characteristics (in number and heterogeneity of participants), and it is not possible to assume a 'standard audience' as in official courses at educational institutions. ALT encourages high completion rates and high learning performance in MOOCs, and several adaptive frameworks are emerging. Clark (2013, p.4) presents an adaptation of the MOOC in CogBooks as the leading technology used for massive personalized on-line learning, and he says 'Adaptive engines can help guide you quickly to your learning objectives …. By knowing what you have done, what others have done and where you need to go, adaptive learning can guide you through a network of content.' Sonwalkar (2013) proposes an adaptive system with web services and computer architecture, which relies on diagnostic assessment adapted to five learning styles. In addition, Onah and Sinclair (2015) recommend systems by which users create their own learning paths, making choices according to their own goals and preferences. Teixeira et al. (2016) adds to the pedagogical model for MOOCs, with content adaptation to accommodate initial knowledge and the device used. Through these approaches, very diverse customization factors are considered, such as the possibility of choosing the language of the resources, or that the activities should be adapted to the learner's country of origin (Daniel, Vázquez Cano & Gisbert, 2015). From our own perspective, some of these factors, such as the choice of the language or the device used for online access, could be better understood as facilitators of learning than as indicators of personalization of learning.

The works mentioned consider different aspects of personalized learning; they speak of the adaptation of contents, the choice of paths to different learning objectives, or styles and preferences, and some of them propose specific and sophisticated technologies for implementing these adaptive techniques. In order to identify the most important aspects of adaptive learning that can help teachers in designing adaptive MOOCs; this paper proposes a construct with six indicators of adaptivity in MOOCs. It aims to discover which adaptive characteristics are most in demand by MOOC participants. The six indicators provide an initial indication as to what most authors consider the most important aspects of personalized learning. They include learning pace, different learning paths depending on participant preferences, the results of previous activities (for example, the measurement of knowledge or skills), interest groups, profiles groups and social collaboration.

The construct will be used to study whether participants in a MOOC prefer to use techniques that adapt the learning to the MOOC participants. This paper will examine whether the proposed construct for adaptivity of MOOCs presents a consistent scale. In addition, it will study which adaptivity indicators are more acceptable to the MOOC participants, and whether the performance or completion of other MOOCs previously influences the participant's perception of the value of the proposed construct.

This study is part of a more extensive research program that has the aim of improving the completion rate of MOOCs by using the indicators proposed here as an adaptive system in an open-source e-learning platform that is much used and is very accessible in academic institutions. The adaptive indicators and the adaptive system used will allow huge accessibility to participants and designers and provide for transferability to any context, ahead of more sophisticated solutions.

The next section presents the conceptual model with the adaptive indicators proposed and the technology used. The research method is then explained with the problem statement, research questions, variables and research context. The results

Please cite this article in press as: Lerís, D., et al., Validation of indicators for implementing an adaptive platform for MOOCs, Computers in Human Behavior (2016), http://dx.doi.org/10.1016/j.chb.2016.07.054