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Validation of indicators for implementing an adaptive platform for MOOCs

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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,

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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 section will provide answers to the research questions and the paper will end with a discussion and conclusions.

2. Conceptual model

The proposed conceptual model includes three of the four fundamental facets of personalized learning: logistics, methodology, technology and economics (Sein-Echaluce, Fidalgo-Blanco, García-Peñalvo & Conde, 2016). The economic aspect is the responsibility of the institutions. In the learning environment, 'Macro adaptive learning' refers to the customization of learning paths at the institutional level (namely, the 'logistics of learning'). An example of this is happening at the University of Maine, Presque Isle, which allows students to choose their personal learning itineraries and to advance at their own pace (UMPI., 2016). These itineraries include ambitious technological solutions such as learning analytics, big data and technology enhanced learning within their recommended systems (Bousbahi & Chorfi, 2015). The Horizon Report 2015 (Johnson et al., 2015), in speaking about ALT, comments that 'these artificial intelligence systems are able to learn how people learn and adapt learning paths to the specific needs of each person.' If the application context is changed, 'Micro adaptive learning' adapts to the methodology of the course, where the teachers are the involved agents who design and implement the course for the students or participants.

As already mentioned, the goal of personalized learning is to help students determine their strategy and learning pace, and in addition, meet the learning needs, interests, wishes or specific cultural backgrounds of individual students. The earlier work of this research group, involving traditional online courses, was focused on the following dimensions: learning pace, accessibility to resources being dependent on the choice of the participant or on the results of previous activities (for example, measuring their knowledge or skills), interest groupings and profiles (Lerís & Sein-Echaluce, 2011; Lerís López, Vea Muniesa & Velamazán Gimeno, 2015; Sein-Echaluce et al., 2015), and the combination of these with social collaboration. The goal of this work was to improve the average completion rate for MOOCs (Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2015; Sein-Echaluce et al. 2016). This work has enabled us to propose adaptivity indicators that conform to the current adaptive methodology.

Combining all these features, this paper proposes an adaptive model for MOOCs that includes three of the fundamental facets of personalized learning: Concerning the logistics of learning, a set (Campus) of 'adaptive MOOCs' (hereafter called aMOOCs) allow participants to self-regulate their time in doing whichever adaptive MOOCs they choose, provided it is within a particular period (four months). Regarding the methodological aspect, each aMOOC includes different adaptive techniques (based on adaptivity indicators), which consider the learning pace, interests and objectives of participants (Sein-Echaluce et al., 2015). In addition, in this paper some related adaptive assessment indicators are introduced, but only at a basic level, based on the cognitive preferences of participants, versus more sophisticated recommendation systems (Bousbahi & Chorfi, 2015; Edu-Trends, 2014). With respect to the technologies, an open and easy-to-use adaptive system is proposed that ensures the transferability and accessibility of the adaptive methodology.

Taking all the above into account, the next subsection presents the six proposed adaptive indicators that, in the opinion of the authors, allow the creation of a MOOC that adapts to the learning pace of each participant, as well as to his/her characteristics, interests, preferences, goals and progress. At the end of the section, the adaptive system considered for the proposed adaptive model will be described.

2.1. Adaptivity indicators for MOOCs

The proposed indicators include skills related to self-regulation of learning; these are very important for learning in general and essential when following online courses with the characteristics of MOOCs (i.e. massive and heterogeneous) (Littlejohn, Hood, Milligan, & Mustain, 2016). Skills related to collaboration are also necessary for cMOOCs (Downes, 2008), as are assessments, which are an important factor in learning design (Guardia, Maina, & Sangrá, 2013). The work of Littlejohn and Milligan (2015) focussed attention on the self-regulation required by professional learners in MOOCs, but also provided useful tools for encouraging self-regulated learning in MOOCs generally. These authors motivate for a design team which 'enables instructional designers to question their design decisions and provides possible interventions that may improve their design' and which could potentially be adapted to other contexts. Guardia et al. (2013) presents a set of learning design principles as seen from the learner's perspective. These focus on 'empowering learners in networked environments to foster critical thinking and collaboration, to develop competence based outcomes, to encourage peer assistance and assessment through social appraisal, providing strategies and tools for self-regulation, and finally using a variety of media and ICTs to create and publish learning resources and outputs.' (p.1).

The six proposed indicators cover the construct 'Adaptivity in a MOOC' and respond to the needs of personalization as broadly defined and as recommended for a positive influence on learning. The first three indicators focus on the promotion of skills related to the self-regulation of learning, while the last three indicators relate to cooperative skills, both necessary aspects in improving the motivation of participants in MOOCs and decreasing dropout rates.

Indicator 1. *Course contents / activities are accessible depending on the choice of the participant or on the results in activities previously evaluated.*

The fact that trainees can choose between different learning activities, depending on their preferences, clearly affects their performance and is reflected in the extensive literature on learning styles, thinking styles, etc. The proposal that learning activities should depend on the results of previous learning, is a condition widely used in traditional teaching, in which teachers include reinforcement activities for students who suffer from lack of knowledge, and provide motivating and challenging activities for students who show high levels of knowledge and skills (Lerís & Sein-Echaluce, 2011; Sonwalkar, 2013). A study by Hood, Littlejohn, and Milligan (2015) 'provides an insight into how an individual's context and role may impact their learning behaviour in MOOCs', which suggests that the convenience of offering different itineraries is dependent on the learner characteristics, and automatically depends on the progress of participants, or alternatively is by their own choice.

Indicator 2. *Course content / activities are accessible depending on the working pace of participant. There is no fixed timetable for accessing contents nor are all contents offered at the same time.*

The simultaneous access of participants to all the contents/activities in a MOOC may cause problems to learners because they can find too many resources at the same time and therefore self-regulation is more difficult. At the same time, the teacher can find it an impossible task, or one requiring excessive effort, to meet the different paces at which learners work through the same course, even when the number of participants is not very high (Watters, 2015). For these reasons, the majority of MOOCs include temporary restrictions on programs, and in some cases, these do

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not match the availability of participants. The indicator 2 facilitates to students to self-regulate the time needed to do the tasks in any online course, even though they are following the academic paths through the logistics of some formal learning (UMPI, 2016) or else in non-formal learning through adaptive MOOCs (Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2016).

Indicator 3. *The participant can choose between different levels of difficulty in the contents / activities to reach different learning objectives.*

The personalization of learning must cover the learning needs, interests, aspirations, etc. of the participants (Johnson et al., 2015), so they can choose among different levels of difficulty in the content/activities and thereby reach different learning objectives (Onah & Sinclair, 2015).

Indicator 4. *Participants are organized by same area of interest / same background / same level of experience, to debate in specific forums.*

The organization by similar interest groups, similar levels of knowledge or from the same background, has always been a motivation for students and benefits their performance. The arrival of the Internet and social media technology has facilitated the creation of learning communities. These are being included increasingly in both formal and non-formal (the MOOCs) academic life, and they are improving profits (Fidalgo-Blanco, Sein-Echaluce, García-Peñalvo & Esteban Escaño, 2014; García-Peñalvo, Cruz-Benito, Borrás-Gené, & Blanco, 2015; Cruz-Benito, Borrás-Gené, García-Peñalvo, Fidalgo-Blanco, & Therón, 2015a).

Indicator 5. *Participants can choose between different methods of evaluation (self-evaluation, peer evaluation, etc.).*

This refers to the type of assessment that participants in a MOOC prefer, and matches their thinking styles (Núñez et al., 1997). The so-called Computerized Adaptive Tests (CAT) allow adaptive assessment with a collection of questions that are selected according to the skills of the individual (Edu-Trends, 2014).

Indicator 6. *The need for peer assessment is also organized according to area of interest / background / level of experience.*

This need arises more specifically in courses where participants have heterogeneous profiles. The heterogeneity can cause serious inequalities in the evaluation criteria because the people evaluated can vary in age from 16 to 85 years, for example, and come from very different backgrounds (Fidalgo-Blanco, Sein-Echaluce & García-Peñalvo, 2015). These factors, together with others identified by Suen (2014), produce distrust in the participants about the seriousness and reliability of the assessments; so it is necessary to initiate other activities and to create rubrics.

2.2. Adaptive system

A common feature of most ALT has been the inclusion of sophisticated devices, based on artificial intelligence, which, however, still fail to create a 'friendly' and 'easy to use' environment for users, i.e. for the designers and participants in courses. In such an environment, the teacher achieves personalization of learning through using a good adaptive methodology that needs the support of the ALT. Note that, in the micro (non-institutional) environment, the teacher is an expert in their own area of knowledge, but is seldom an expert in general technology, nor in the specific technology that is required for using certain adaptive systems. This has been the main reason for the failure of some AHS: they have not arrived at an easy technology for the teachers to use. As Lemke (2013) noted, the intelligent learning systems need to embrace three elements: technology that is accessible for teachers, learning analytics with big data, and studies on the cognitive aspects of how people learn.

The framework proposed for our general research, into which this work fits, is based on the i-MOOC platform (2016), developed throughout a collaboration agreement in 2013 between the Technical University of Madrid and the University of Zaragoza, and using the open-source e-learning platform Moodle (version 2.8) (Moodle, 2016). In 2015, the University of Salamanca joined in with this agreement.

The interdisciplinary research group of authors has avoided sophisticated solutions and has implemented many adaptive techniques by using open-source e-learning platforms that are in widespread use (such as Moodle) and other external tools that allow the integration of functionalities such as learning analytics. This choice has helped to erase the technological barriers to teachers and to implement adaptive methodologies through an accessible and easy e-learning platform. This technological solution allows total transference and applicability of the adaptive methodologies (Hernández, Fernández & Sein-Echaluce, 2015; MoodleMOOC, 2016).

Previous studies have shown that the Moodle LMS is versatile and flexible and can be adapted to the required navigation and content of any course. Some technological solutions, integrated within the same LMS, have been developed to complete the shortcomings of previous versions of Moodle (v1.x) and to provide it with adaptive functionality, such as the development of eLessons by Komlenov, Budimac, and Ivanovic (2010), or the CICEI Conditionals (CICEI, 2016) whose applications were studied and reported in previous work (Lerís & Sein-Echaluce, 2011; Fidalgo, Sein-Echaluce, Lerís & Castañeda, 2013). However, the version 2.8 includes sufficient features within its basic installation for teachers to create simple and affordable instructional courses. In contrast, the difficulty, that teachers experience in using most of the developed AHS and the enormous effort that is required by teachers in handling these, are major reasons for their limited acceptance, as has been mentioned before (Lerís López, Vea Muniesa & Velamazán Gimeno, 2015).

Other studies have suggested the possibility of integrating an LMS into the external software, thereby creating learning analytics that provide complementary data to the platform log. For instance, previous works have included learning analytics frameworks as complementary tools for studying interactions in forums, wikis, web resources, videos, quizzes and assignments as included in the e-learning platforms (Clow, 2013; Conde, Hernández, García-Peñalvo & Sein-Echaluce, 2015; Fidalgo-Blanco, Lerís, Sein-Echaluce & García Peñalvo, 2015). This constitutes a variant on the emerging e-learning ecosystems that contain adaptive systems for managing online courses (García-Peñalvo et al., 2015) and MOOCs in particular (Cruz-Benito, Borrás-Gené, García-Peñalvo, Fidalgo-Blanco, & Therón, 2015b). Ecosystems include different technological tools for both general and specific purposes, such as learning analytic techniques. They allow institutions to analyse the actions of their students in academic tasks, and teachers can analyse interactions between students in online learning activities, and this can serve to improve methodologies, enabling active learning, identifying students at risk and assessing achievements (Iglesias-Pradas, Ruiz-de-Azcárate & Agudo-Peregrina, 2015; Conde et al., 2015; Fidalgo-Blanco, Sein-Echaluce, García-Peñalvo & Conde, 2015).

3. Research method

With the overall goal of improving performance rates on MOOCs, the present study intended to find out whether

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participants in a MOOC considered it interesting to use techniques that adapt the learning to the students participating in the MOOC. Therefore, the participants in a set of aMOOCs (Sein-Echaluce et al., 2016) were requested to answer a questionnaire designed ad hoc. In fact, this activity was the only one that participants saw when they entered for the first time in the campus aMOOC, and it was necessary for them to answer it before being given access to any aMOOC.

3.1. Research questions

The following research questions are intended to examine the proposed conceptual model of adaptivity of a MOOC from the student's perspective.

RQ1. Considering the proposed adaptive indicators of a MOOC separately: do participants value them equally?

RQ2. Considering the scale of adaptivity of a MOOC: are the questionnaire's response data consistent?

RQ3. Considering the scale of adaptivity of a MOOC: does the data set confirm the unidimensionality of the scale, and if so, which characteristics reflect the scores of the participants?

RQ4. Considering the variable of having or not having previous experience with MOOCs: does this variable influence the scores on the proposed adaptivity scale and the scores of the items taken separately?

RQ5. Considering the participants who have had the most success with MOOCs (those who have completed all the MOOCs that they began): do they value the proposed adaptivity concept differently from the other participants?

3.2. Study variables and measuring instrument

The target study variable is named ‘basic adaptive MOOC’ and it is the sum of the scores of six items, which refer to the six indicators selected by the authors to characterize the concept of a basic adaptive MOOC. A questionnaire was designed containing six items, tagged 1 to 6, with values on a Likert scale of four levels: ‘No agreement’, ‘Little agreement’, ‘Rather agree’ and ‘Strongly agree’ (scored from 1 to 4, respectively). The wordings are shown below:

Item 1. *I would like it if the course offered me different activities depending on my choice or on my assessment results.*

Item 2. *I would like to access the content/activities according to my own rhythm of work and not access the contents according to a default calendar.*

Item 3. *I would like to choose between different levels of difficulty in the content/activities to achieve different learning objectives.*

Item 4. *I would like to be associated with different interest groups (same area, same level of experience and so on) and to discuss in separate forums.*

Item 5. *I would like to choose between different methods of evaluation (self-evaluation, peer review, etc.)*

Item 6. *I would like peer review to be organized according to interest groups (same area, same level of experience and so on).*

The dependent variable ‘basic adaptive MOOC’ was analysed in relation to independent variables from previous experience in MOOCs. Specifically, there are two factors, one is ‘to have begun, or not, any MOOC’, and the other is ‘to have completed, or not, every MOOC begun’. To collect the data for these two variables the following three questions were added to the questionnaire:

- Have you started any MOOC before the current one? Response options: No, Yes. Variable name: MOOCsprevious.
- How many MOOCs have you started, excluding the current one? Response options: Integer numbers from 1 to 10, and the option ‘more than 10’. Variable name: nMOOCsprevious.
- Of the MOOCs you've previously started, how many have you finished? Response options: Integer numbers from 1 to 10, and the option ‘more than 10’. Variable name: nMOOCsfinished.

3.3. Research context: aMOOC campus

The i-MOOC platform used for this research experience may be composed of ‘n’ virtual campuses, and each virtual campus may contain a set of aMOOCs. In this case, the research was carried out with the participants in the first edition of the ‘Educational Innovation MOOC Campus’ (hereinafter EIMC) composed of four adaptive MOOCs. This first edition of the EIMC was active during the four months, November 23rd, 2015 to February 28th, 2016, and the available aMOOCs were:

- Practical fundamentals of educational innovation (15 h)
- Flip teaching (20 h)
- Learning communities (15 h)
- Teamwork competence development (30 h)

In previous research, the authors have presented ‘adaptive pills’ (adaptive actions) during the implementation of the aMOOCs (Sein-Echaluce et al., 2015), which are a slight variations on the six adaptive indicators for the conceptual model as defined here. Different combinations of those adaptive pills set up the logistic, methodological and technological models implemented in the aMOOCs. Some of the Moodle tools were used as adaptive facilitators, such as ‘access restriction’, ‘finalization condition’, ‘groups’ and ‘groupings’, as well as several plugins that choose a group or generate certificates for the course (Sein-Echaluce et al., 2016).

In order to carry out this empirical research, it was decided, on January 22, 2016 (before ending the EIMC), to consider the enrolees who had completed the initial survey about the participants' characteristics and their perceptions about possible adaptivity options to be included in future aMOOCs, that is, the items mentioned in the previous subsection.

The sample size was 475, of which 222 (46.74%) were men and 253 (53.26%) were women. The majority of participants (308; 64.8%) were between 36 and 55 years (see Table 1). Concerning country of residence, 211 participants were residents of America, all of them in Ibero-America except one, and 264 resided in Europe, 253 of whom were in Spain.

The participants were all people interested in educational innovation (the subject of the aMOOCs campus), and most of them were middle aged and lived in a Spanish-speaking country.

Table 1
Distribution of the sample by age.

Age	Frequency	Percentage of frequency
Up to 25	31	6.5%
From 26 to 35	89	18.7%
From 36 to 45	151	31.8%
From 46 to 55	157	33.1%
More than 55	47	9.9%
Total	475	100%

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4. Results

This section first discusses the six items and their possible associations. Then a dimensional analysis of the scale of 'basic adaptive MOOC' is conducted, and its internal consistency is established using Cronbach's alpha, and the principal components of the correlation matrix are then calculated. Before analysing the dimensionality of the scale, the characteristics of the distribution of the sum of the six items (the variables that measure the proposed adaptivity of a MOOC) are studied. Finally, the influence of the two factors on that variable are analysed, both of which relate to the previous experience of participants in such courses.

4.1. Analysis of the proposed adaptive indicators of a MOOC, taken separately (RQ 1)

First, we show the distribution of responses to the six items that make up the proposed scale of adaptivity of MOOCs and their corresponding statistics, and then we analyse the homogeneity of those distributions, seeking to answer the first research question.

The distribution of the percentage of responses for each of the six variables of adaptivity appears in Table 2, in which the most frequent option is highlighted in bold. Because the frequency of the responses is greatest in the two top-level options, the value of the odds on frequency of the level 'Strongly agree' in relation to the cumulative frequency of the other three levels, 'Strongly disagree', 'Disagree' and 'Agree' is calculated. The results of these odds, shown in Fig. 1, reveal two facts:

- The list of items in descending order of odds is item 2, item 3 item 1, item 5, item 4 and item 6.
- The high value of the odds on item 2 indicates that this adaptivity feature is that most valued by participants. In fact, they marked 'Strongly agree' the possibility of accessing content according to their personal pace of work (item 2), almost twice as often as the three lower order options combined.

Fig. 2 presents the averages of each item together with the overall mean value (3.39). It can be seen that the means of items 1, 2 and 3 are above the overall mean value, whereas the other three are below. The order of items, according to their average scores, is equal to descending order of odds.

In summary, the results of the above descriptive analysis reveal the following:

- The list of items in descending order of importance (for both odd and mean value) appears to be: item 2, item 3, item 1, item 5, item 4 and item 6.
- The participants seemed to value the first three items more highly than the last three (falling as they do above and below the overall mean).

To find out if these apparent differences between items are

Table 2
Distribution of the percentage of frequency of each item.

Item	Level of agreement with the statement			
	Strongly disagree; 1	Disagree; 2	Agree; 3	Strongly agree; 4
Item 1 – Y1	0.6%	4.4%	**47.6%**	47.4%
Item 2 – Y2	0.6%	5.9%	28.0%	**65.5%**
Item 3 – Y3	0.4%	5.9%	41.3%	**52.4%**
Item 4 – Y4	0.8%	13.7%	**44.2%**	41.3%
Item 5 – Y5	1.1%	8.2%	**46.3%**	44.4%
Item 6 – Y6	2.3%	9.9%	**47.6%**	40.2%

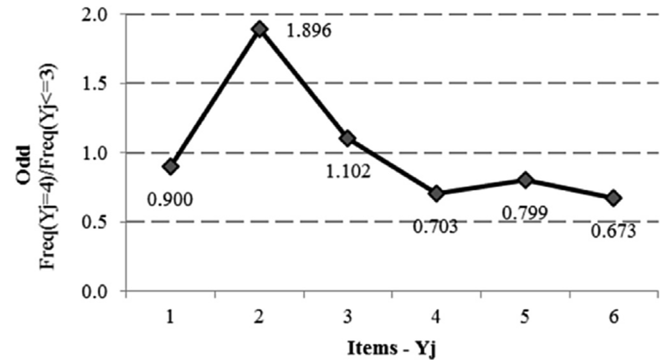

Fig. 1. Graph showing the odds for the upper level of agreement of each item against the grouping of the other three lower levels.

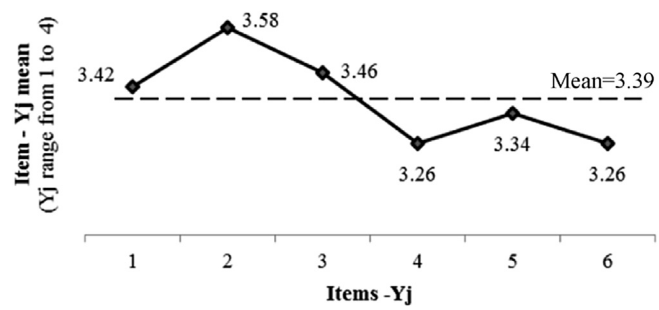

Fig. 2. Graph of the mean values for each item.

statistically significant, the homogeneity of the distribution of the items is studied. That is, the null hypothesis is tested for no difference in the distribution of the six items, against the alternative hypothesis that the distribution of at least one of the variables differs from any other. To do this, the non-parametric Friedman test was applied. The results achieved with the R software are Friedman chi-squared = 142.06, df = 5, p-value < 2.2e-16. Therefore, the null hypothesis is rejected; that is, there are pairs of variables that are distributed differently. Thus, it was necessary to carry out some procedure post-hoc to identify the differences. Two types of multiple comparisons were performed:

- Comparison of ranges offered by the order friedmanmc ( ) of the R software package 'pgirmess'.
- Wilcoxon test for paired samples with the adjusted p-values based on the Bonferroni procedure.

The common results of both methods are displayed in Fig. 3. In this figure, the items are grouped such that each group contains those items with homogeneous distribution, while differing from the items in the other groups. Moreover, they are ordered as arrived at both through comparing the odds of their upper level and their means.

In this way, three groups of items emerged. The first one contains item 2 and item 3 (one test does not show a difference between them although the other does). These two items describe adaptive features of the greatest significance for participants in the MOOC: to allow self-paced learning and to support different

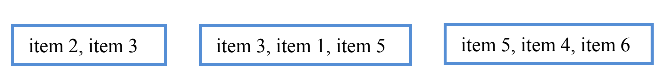

Fig. 3. Groups of items with homogeneous distributions.

learning objectives according to the level of the participant. These factors relate to the theory of self-regulation of learning that Littlejohn et al. (2016) indicate relates strongly to the motivation of participants. The intermediate block consists of items 1, 3 and 5: these describe common features around the 'choice' the participants have in determining which following steps to perform in the MOOC. Finally, the last group consists of items 4, 5 and 6; these items share characteristics related to cooperative activities, such as forums and peer assessment.

4.2. *Analysis of the internal consistency of the scale proposed to measure the adaptivity construct related to a MOOC (RQ2)*

In this subsection, we explore the agreement between the six questionnaire items designed to measure the construct of basic adaptivity of a MOOC, and in this way respond to the second research question.

As mentioned before, each four-point Likert item was used to reflect the degree to which the participants agreed with the different statements regarding the adaptive design of a MOOC. The total score, that is, the sum of individual scores given for each item, is intended to measure the adaptivity score for each participant.

It is necessary to analyse the internal consistency between the six items by using Cronbach's alpha and using the survey data collected in the aMOOC campus. The calculations were made using the software R and the results obtained are discussed below.

With regard to statistical internal consistency, and using the results from the sample, the value of Cronbach's alpha for the six items that measure the adaptivity construct is 0.8209. According to the general criteria established by George and Mallery (2003), a statistical value for Cronbach's alpha greater than 0.8 reflects a good internal consistency for a scale. In addition, authors like Nunnally (1978) and Kaplan and Saccuzzo (1982) recommend values above 0.7 for exploratory analyses such as this one; and the acceptable threshold is further lowered to 0.6 by Huh, Delorme, and Reid (2006). Given that the value of the Cronbach's alpha for the scale measuring adaptivity was higher than any of the above thresholds, it can be confidently said that the scores for each item are consistent with the total score.

The statistics for the item-total are shown in Table 3. In the first column, one can see the correlation of each item with the total for the scale. The minimum value of these correlations is 0.496, which is superior to the threshold of 0.35 as identified by Cohen and Manion (1990), and superior to 0.4, as more recently established by Gliem and Gliem (2003), who consider that any item below that threshold should be scrapped or reformulated. In addition, in the last column of Table 3, the Cronbach alpha values with one item removed are included. It was found that the removal of any one item did not improve the alpha value.

In summary, the application of the scale to measure the adaptivity in the sample formed by the participants in the aMOOC campus, gave rise to a Cronbach's alpha value that allows one to say that internal consistency is good and, in addition, the item-total values confirm that no one item should be removed from the scale.

Table 3
Total-element statistics.

Item	Correlation item-total	Crombach's alpha, if the ítem is removed
Item 1	0.5475	0.8006
Item 2	0.496	0.8106
Item 3	0.5852	0.7929
Item 4	0.6299	0.7828
Item 5	0.6269	0.7836
Item 6	0.635	0.7817

4.3. *Dimensional analysis of the questionnaire items proposed to measure the adaptive construct of a MOOC (RQ3)*

Although the internal consistency of the scale was proven, this does not guarantee one-dimensionality. In order to know more about the dimensions of the scale used to measure the basic adaptivity of a MOOC (research question 3), a principal component analysis was performed on the correlation matrix. In this way, we would be able to identify the meaningful underlying variables.

The results of the principal component analysis performed with R are shown in Tables 4 and 5. In Table 4, the loadings or coefficients of the principal components are shown (normalized eigenvectors of the correlation matrix), and in Table 5, the measures of the importance of each component (proportion of explained variance).

The scree plot in Fig. 4 clearly shows the predominance of the first eigenvalue relative to the others. Therefore, in accordance with the scree test and with Kaiser's stopping rule, only the first factor (the one greater than 1) should be considered in the analysis. However, we decided to retain three components because they cumulatively explain 78% of the variance, which we consider enough for the exploratory nature of this work.

The first principal component explained almost 53% of the sum of variances of the items (see Table 5). The first column of Table 4 shows the coefficients, all of them with a negative sign, of the linear combination of the original items that result in the first principal component. Once the signs are changed, we have:

$$\begin{aligned} Comp1 = {} & 0.39 \cdot Item1 + 0.36 \cdot Item2 + 0.41 \cdot Item3 + 0.43 \cdot Item4 \\ & + 0.42 \cdot Item5 + 0.43 \cdot Item6 \end{aligned}$$

Our interpretation is that this first component reinforces the idea that the items were built, that is, their sum gives a measure of the construct of basic adaptivity of a MOOC. Therefore, it is confirmed that the scale was designed to classify individuals according to their interest in adaptivity in a MOOC.

The second principal component is far less relevant than the first because it meets only 15% of the total variance (see Table 5). It is another combination (coefficients in Table 4) of the original variables, and sets the first three variables against the last three, as shown in its formulation below. Hence, we can say that this second factor opposes the three characteristics of self-regulation against the three characteristics of cooperation.

$$\begin{aligned} Comp2 = {} & (0.23 \cdot Item1 + 0.59 \cdot Item2 + 0.43 \cdot Item3) \\ & - (0.35 \cdot Item4 + 0.35 \cdot Item5 + 0.41 \cdot Item6) \end{aligned}$$

The third component, which explains little more than 10% of the total variance (see Table 5), is the following combination of the variables

$$\begin{aligned} Comp3 = {} & (0.79 \cdot Item1 + 0.15 \cdot Item4) - (0.43 \cdot Item2 \\ & + 0.08 \cdot Item3 + +0.40 \cdot Item5 + \ 0.03 \cdot Item6) \end{aligned}$$

Given that the coefficients of items 3, 6 and 4 are very small, it seems that this component sets the first item against the second and fifth, considering that item 1 has almost twice as much weight as the other two. In other words, the third dimension sets the adaptivity of content against the adaptivity of collaboration activities.

Finally, the sum of the items' scores is the value of the variable 'basic adaptive MOOC', and it sorts the participants according to the first dimension. The values of that variable run from 6 to 24, and the quartiles of the variable 'basic adaptive MOOC' are shown in the box plot of Fig. 5. It can be observed that the interquartile range (from 18 to 23) is situated in the upper part of the possible values of the

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Table 4
Component loadings.

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Item 1	−0.387517	0.2342913	0.7923807	0.28256468	0.2597978	−0.140474
Item 2	−0.359713	0.5888025	−0.433023	0.42095898	−0.3277335	−0.2275811
Item 3	−0.408347	0.4287671	−0.076918	−0.6590496	0.1823992	0.41938
Item 4	−0.431933	−0.347652	0.1452285	−0.4068933	−0.5648708	−0.4322497
Item 5	−0.423662	−0.349934	−0.395482	0.05102633	0.6548845	−0.3319239
Item 6	−0.433168	−0.413839	−0.034781	0.37475131	−0.2094607	0.6749674

Table 5
Importance of components.

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standard deviation	1.7796354	0.9547923	0.7956532	0.72093977	0.65054075	0.58757823
Proportion of variance	0.5278504	0.1519381	0.1055107	0.08662569	0.07053388	0.05754136
Cumulative proportion	0.5278504	0.6797884	0.7852991	0.87192476	0.94245864	1

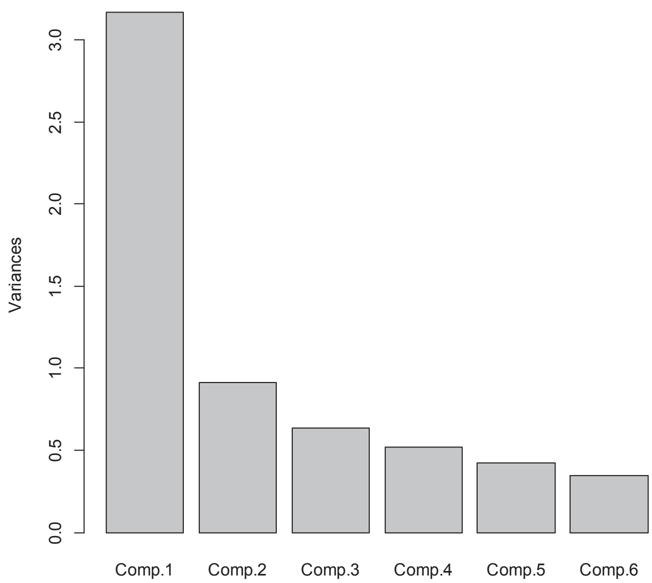

Fig. 4. Scree plot (eigenvalues).

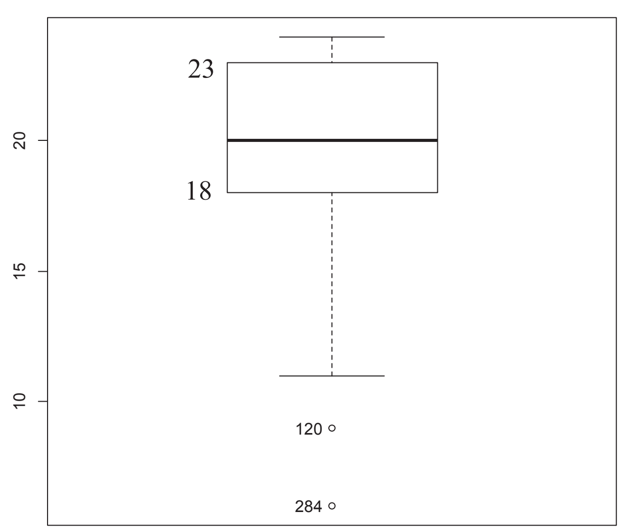

Fig. 5. Boxplot variable 'basic adaptive MOOC'.

variable, and that the median, 20, is closer to the top than to the bottom of the box plot. Therefore, the scores of the 'basic adaptive MOOC' accumulate in the higher values of the variable, and we can say that the proposed adaptivity of a MOOC is strongly preferred by the participants in the aMOOC campus.

4.4. Analysis of the influence of previous experience in MOOCs in the variable 'basic adaptive MOOC' (RQ4)

To explore the influence that participants' previous experience in MOOCs may or may not have had on their interest in the adaptivity of a MOOC, a question was included in the questionnaire with the following wording: 'Have you started on any MOOC prior to the current one?' The replies were coded into the dichotomous variable ('yes' or 'no'), named 'MOOCsprevious'.

Table 6 shows the distribution of the sample for each category of the variable 'MOOCsprevious'. One can see that a high percentage of participants (72.84%) had previously enrolled in some other MOOC.

In Fig. 6, it can be observed that there may be a significant difference in the means of the variable 'basic adaptive MOOC', according for each of the groups into which participants were classified according to whether or not they had previously begun some other MOOC.

Given that the variable 'basic adaptive MOOC' is not distributed as a normal variable (Shapiro-Francia test: $W = 0.92352$, p-value = 4.145e-13 and Kolmogorov-Smirnov test for normality: Kolmogorov distance = 0.11074, p-value = 1.744e-05), we used the non-parametric Wilcoxon text (Hines & Montgomery, 1990) to test the null hypothesis for equality of the medians in the two population groups, according to the 'MOOCsprevious' factor.

The results of applying the Wilcoxon test are as follows: $W = 27{,}588$, p-value = 6.339e-05. Therefore, it is rejected that the variable 'basic adaptive MOOC' is independent of factors due to having participated in some other MOOC before being enrolled in the current aMOOC campus. In other words, those participants who had never before participated in a MOOC tended to consider adaptivity as a quality of greater value than those who already had prior experience.

Because the data does not have a normal distribution, we used Cliff's delta (Cliff, 1993) to quantify that difference between the two groups. The value of Cliff's delta is 0.24, and it represents the difference between the probability (0.56) that a randomly chosen participant without experience in MOOCs would have a higher score than a randomly chosen one with experience, and the probability of the opposite (0.32). Moreover, there is a probability of 95% that the true delta value can be found in the interval (0.12203,

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Table 6
Distribution of the sample for the variable 'MOOCsprevious'.

MOOCsprevious: have you started on any MOOC prior to the current one?	Frequency	Frequency percentage
NO	129	27.16%
YES	346	72.84%

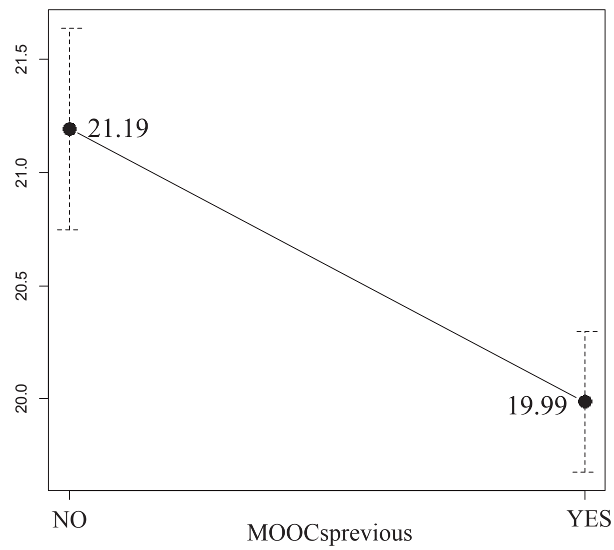

Fig. 6. Graph of the means of the variable 'basic adaptive MOOC', with confidence intervals at 95% for each group of 'MOOCsprevious' factor.

0.34417), hence, the difference between the two groups of participants can be considered small. Although they do not differ much, this effect reveals things that should be the subject of further studies.

We also analysed the items of the scale 'basic adaptive MOOC' separately to find out whether any were distributed differently, depending on the factor 'MOOCsprevious'. Fig. 7 shows the mean values for each item and two insights are revealed. One of these is their 'parallelism' to each other, and the second is the less apparent difference between items 2 and 3.

In order to find out whether there were significant differences in the distributions of each item according to the factor 'MOOCsprevious', the non-parametric Wilcoxon test was applied to decide on the homogeneity of the distributions. The results obtained with software R are shown in Table 7. The p-values of items 1, 4, 5 and 6 are less than 0.05, so the null hypothesis is rejected. In contrast, items 2 and 3 are homogeneously distributed, regardless of whether participants had begun some other MOOC.

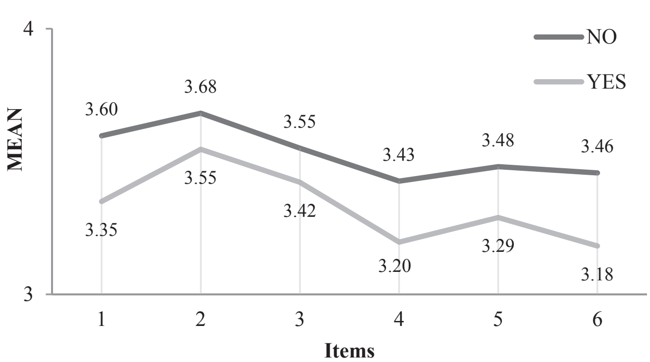

Fig. 7. Graph of the average values of each item according to whether or not participants had previously started on another MOOC.

Consequently, the participants of the aMOOC campus valued equally two items of the proposed basic adaptivity regardless of whether they had enrolled previously in other MOOCs. These items (2 and 3) are two of the three related to competence in self-regulation.

A measure of the difference of the effect size for the other four items (1, 4, 5 and 6), depending on whether or not the participants had previously performed in MOOCs, are the corresponding odds ratio, whose values and confidence intervals are included in Table 7. It is noted that:

- It is at least 37% more likely that a participant without previous experience in MOOCs will value item 1 (different activities depend on my choice or on my assessment results) at a higher level than one who is experienced.
- It is at least 40% more likely that a participant without previous experience in MOOCs will value item 6 (peer review should be separated by interest groups) at a higher level than one who is experienced.

In summary, the group of participants without previous experience in MOOCs valued the basic adaptive design of courses more highly. They especially preferred two adaptive features: that peer evaluation should be carried out by separating students according to their interest groups, and that the course should offer different activities according to choices and learning outcomes.

4.5. *Analysis of the influence of having completed all MOOCs initiated on the evaluation of the proposed adaptivity concept (RQ5)*

In this last subsection, we studied the variable 'MOOCsSuccess', which classifies the participants who had previously begun a MOOC ($n = 346$) into two categories: those who had completed all the courses begun and those who had not. That is, the variable 'MOOCsSuccess' distinguishes between participants with full success in completion of MOOCs and those without this success. The authors calculated this binary variable by comparing the responses of the participants to the questions: *how many MOOCs have you started excluding the current one?* and *How many MOOCs have you finished?*

The mean values of the variable 'basic adaptive MOOC' in both groups, according to the factor 'MOOCsSuccess', and the corresponding central moments of orders 1, 2 and 3 are shown in Table 8. Note that both distributions have almost equal mean values (hypothesis accepted by the Wilcoxon test: $W = 15{,}066$, p-value $= 0.7424$), and a similar dispersion (hypothesis supported by the Levene test: F-value $= 1.863$; p -value $= 0.1732$), with asymmetry in both cases toward the higher values of the variable, although different behaviours in relation to the concentration around the mean. Therefore, statistical analysis confirms that the distribution of the variable 'basic adaptive MOOC' is independent from the factor of have completed all MOOCs previously begun.

Finally, it was also found that there were no significant differences in the distribution of any of the six adaptivity items considered in this study. Fig. 8 shows the mean values of these items for each study group, it highlights the extraordinary equality between

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Table 7
Values of Wilcoxon statistic and odds ratio for each item for each group of 'MOOCsprevious' factor.

Ítem	Wilcoxon test	Odd ratio (No/Yes)	Odd ratio IC 95%	
			Lower	Upper
Ítem 1	W = 26,818, p-value = 0.000136	2.070	1.3709	3.1270
Ítem 2	W = 24,500, p-value = 0.04943	1517	0.9746	2.3606
Ítem 3	W = 24,320, p-value = 0.08941	1315	0.8746	1.9763
Ítem 4	W = 26,114, p-value = 0.00186	1741	1.1574	2.6178
Ítem 5	W = 25,508, p-value = 0.007799	1652	1.0998	2.4818
Ítem 6	W = 26,760, p-value = 0.0002398	2111	1.4009	3.1825

Table 8
Overview of the variable Adaptivity in a MOOC for each group of 'MOOCsSuccess' factor.

MOOCsSuccess	Mean	Standard deviation	Coefficient of variation	Asymmetric coefficient	Kurtosis	n
No	20.06	2.73	0.14	−0.34	−0.26	153
Yes	19.93	3.12	0.16	−0.70	1.52	193

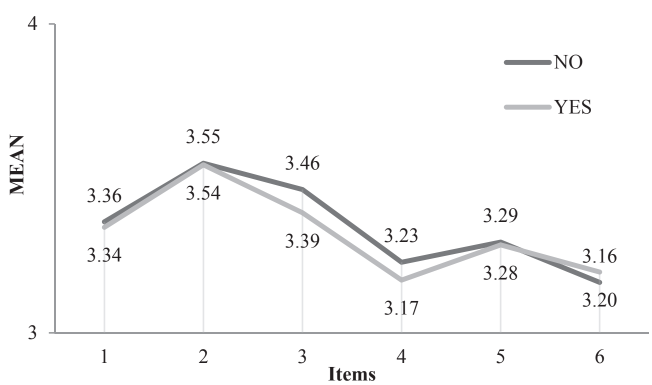

Fig. 8. Mean values of each item per group of the factor of 'MOOCsSuccess'.

these means, an equality that is corroborated by the Wilcoxon test with p-values much higher than 0.05. Consequently, it must be accepted that the six items are distributed equally, regardless of whether participants had finished all MOOCs begun.

Therefore, adaptivity is not a feature that users of MOOCs who have completed all of them value differently from those who have not.

5. Discussion

Now we proceed to answer the research questions given in section 3, according to the results presented in the previous section.

RQ1. *Considering the proposed adaptivity indicators of a MOOC separately: do participants value them equally?*

The statistical analysis carried out has revealed that the six items are not distributed homogeneously in the sample. In fact, if they are ordered according to their mean values and are then grouped into groups of items homogeneously distributed, we will see the image shown in Fig. 9. That is, there are significant differences in the assessment of the six characteristics of adaptivity in a MOOC, and the value given to item 2 is especially highlighted, followed by item 3. As a result, the participants in the aMOOC campus point out that the two adaptive features they find most valuable in the courses are those by which the pace of the work is not imposed (item 2) and by which there are different levels of difficulty, making it possible to achieve different objectives (item 3). Both these indicators are included in most of the customization definitions included in this work. In addition, items related to evaluation (4, 5 and 6) are the lowest rated, consistent with the idea that MOOCs using peer assessment tend to have lower course completion rates (Jordan, 2013).

RQ2. *Considering the scale of adaptivity of a MOOC: are the questionnaire's response data consistent?*

An analysis of internal consistency has shown that the answers given by the participants to the six questionnaire items are sufficiently related. We conclude, therefore, that these items measure characteristics of the same construct, and their sum is a value that represents the proposed adaptivity concept in a MOOC.

RQ3. *Considering the scale of adaptivity of a MOOC: does the data set confirm the unidimensionality of the scale, and if so, which characteristics reflect the scores of the participants?*

In addition to the previously mentioned conceptual homogeneity, a principal component analysis has been conducted. It was observed that the first component, which explained almost 53% of the sum of variances of the items, is a weighted sum with item loadings about the same. Therefore, the dimension of greater variance is precisely the sum variable 'Adaptivity in a MOOC', a fact that supports the one-dimensional character of the proposed scale. The second and third dimensions emerge as groupings of items, which reveal specific characteristics about them. In fact, the second dimension sets the first three items, describing characteristics of overall adaptive design, against the other three, pointing to more specific aspects related to customization activities. The third dimension, in our view, sets item 1, which states that the control of

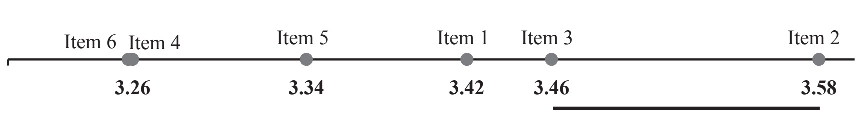

Fig. 9. Grouping of items with statistically homogeneous distributions.

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the training process is in the hands of the designer, against items 2 and 5, in which the participant self-regulates his or her learning.

At the same time, the variable 'basic adaptive MOOC' is highly valued by the participants; in fact, the mean of the sample is 20.31, the range of the variable being from 6 to 24. Therefore, this remarkable mean highlights the desirability of more extensive studies on the advisability of designing MOOCs based on methodologies of personalization and especially on indicators that define that adaptivity.

RQ4. *Considering the variable of having or not having previous experience with MOOCs: does this variable influence the scores on the proposed adaptivity scale and the scores of the items taken separately?*

The results about the influence of the factors of participation and dropout in MOOCs in the variable 'basic adaptive MOOC', allow us to answer the fourth research question. It is demonstrated that those participants who have not previously begun a MOOC, give a higher value to the quality of adaptivity in a MOOC. The value of Cliff's delta is 0.24, seeming to indicate that the adaptivity of a MOOC is a paradigm shift that would appeal to that segment of the population not already engaged in this type of course.

It has also been shown that items 2 and 3 offer special customization features. Specifically, it has been found that the two groups of participants, those who are beginning their first MOOC and those who already have had some experience, value these two characteristics equally: to allow each participant to move at his or her own pace and to differentiate between levels of difficulty. In contrast, the distributions of the other four items are statistically different.

RQ5. *Considering the participants who have had the most success with MOOCS (those who have completed all the MOOCs that they began): do they value the proposed adaptivity concept differently from the other participants?*

The sample of participants who have had experience of MOOCs is broken down into two classes: those who have been completely successful in this type of course, completing all courses begun, and those who have not completed them all. This differentiation, unlike the previous one, was proved not to be influential in the way the overall value of adaptivity in a MOOC was perceived, or in any of the indicators that composed it. In this regard, Jordan (2014) notes the desirability of considering active participants, and not only those who have completed all activities, when talking about completion rates.

6. Conclusions

In this study, we have proposed a conceptual model of adaptivity in a MOOC, which contains six indicators and from which a questionnaire has been developed with six corresponding items. This model was examined from the students' perspective.

The research was conducted with students from a campus i-MOOC (with four adaptive MOOCs) and with four hundred and seventy-five participants. Most of the participants were middle aged and lived in a Spanish-speaking country. Therefore, the scope of the results is limited, but they can provide information on the value of adaptivity of a MOOC from the students' perspective and can serve as a basis for further studies.

Participants say that they value two of the indicators of the proposed construct of adaptivity for MOOCs, most: these are, the adaptation to the pace of personal work (item 2) and diversity in levels of difficulty offered so as to obtain different objectives (item 3), which represent self-learning strategies strongly linked to motivation. In turn, item 3 links the group formed by items 1, 3 and 5, with common characteristics around the concept of individual 'choice' for participants. Finally, item 5 links with a group consisting of items 4, 5 and 6 which have common characteristics related to cooperation (forums and peer assessment), which, incidentally, are the lowest rated items. All this information brings coherence to the proposed adaptive indicators and shows that participants appreciate more the characteristics of self-regulation of learning, and that assessment, which is outside participants' control, or even cooperation tasks, are usually optional in MOOCs.

The study analyses the dimensions of the proposed concept of basic adaptivity of a MOOC and the internal consistency of the whole scale. As result of the principal component analysis carried out, the authors would point out that the first dimension is the sum of the six items of the proposed scale, and the second is the difference between items related to self-regulation and those related to cooperation. The internal consistency of the scale was statistically evaluated using Cronbach's alpha, with a result greater than 0.8, indicating good internal consistency. Therefore, the agreement between the six questionnaire items and the appropriateness of using the variable calculated by adding together the scores of the six items as a measure of the proposed concept of adaptivity of a MOOC has been proved. Nevertheless, we consider this study to be preliminary and expect it to serve as a model indicating a direction for future research in this area.

It was shown that having previously completed MOOCs generally influences participants toward a lower demand for adaptivity than those participants without previous experience. This opens the possibility for new research into that type of perception, to study whether those who have had experience and know the traditional models of MOOC, where there is no personal attention, do not expect anything more, whereas, the inexperienced see personalized attention as an aid to facing something still unknown.

Among future work and as a continuation of the current study, it is also important to determine the degree of importance that participants in a MOOC give the personalization of learning based on socio-demographic factors: gender, age, geographic area of residence, level of studies and professional profile, and even previous experience of innovation and motivation. Future studies should also consider the impact of adaptivity indicators on the satisfaction and learning of the participants in aMOOC, and on the dropout rate. This would be done through differentiated application of the adaptivity indicators proposed in this study, and specifically of the three options for adaptive actions: free choice of participants, recommendation of the system to participants, and automatic choice of the system.

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