Journal of Computing in Higher Education (2021) 33:85–120
https://doi.org/10.1007/s12528-020-09257-9

Perceived user satisfaction and intention to use massive open online courses (MOOCs)

Irma Pozón-López[1] · Elena Higueras-Castillo[2] · Francisco Muñoz-Leiva[2] · Francisco J. Liébana-Cabanillas[2]

Published online: 15 June 2020

Abstract

The aim of the present work is to contribute to the study of use intention for technologies related to the increasingly popular massive open online courses (MOOCs). Informed by a scientific literature review, the work proposes a behavioral model to explain use intention via various constructs. The results of the analysis verify the effect of user perceived satisfaction and autonomous motivation as the strongest predictors of use intention. The analysis also shows that perceived satisfaction is affected by the quality of the course, its entertainment value and its usefulness. The latter variable is also a major factor in explaining user emotions. The study provides an original focus in the study of perceived satisfaction and MOOC use intention by extending the models proposed in previous published literature in this emerging field.

Keywords MOOCs · Massive open online courses · Use intention · Perceived satisfaction · Structural equation model

✉ Francisco J. Liébana-Cabanillas
franlieb@ugr.es

Irma Pozón-López
irmampl@yahoo.es

Elena Higueras-Castillo
ehigueras@ugr.es

Francisco Muñoz-Leiva
franml@ugr.es

1 Faculty of Business and Economics, University of Granada, Campus Universitario La Cartuja, s/n, 18071 Granada, Spain

2 Department of Marketing and Market Research, Faculty of Business and Economics, University of Granada, Campus Universitario La Cartuja, s/n, 18071 Granada, Spain

Introduction

Behaviours, perceptions and motivations of students in online environments have been studied extensively since the swift expansion of online education for the development of theory and practice (Li 2019; Gupta 2019). Technological and web development have also revolutionized the education sector (Rabin et al. 2019). Here in particular, the options for accessing knowledge have multiplied, while new educational techniques are constantly being generated, along with generalized and specialist academic and professional offers. Examples include courses that are delivered entirely online, or as a complementary online element to traditional learning environments. In the higher education sector in particular, as noted by Daniel et al. (2015), universities are currently addressing the question of how to reach more students at a lower cost, and the online route constitutes an interesting option in this regard.

Higher education institutions, whether public or private, are operating in a market that is increasingly competitive and international in nature (Alexandron et al. 2019; Chang et al. 2019). The use of comparative international rankings such as the Shanghai Ranking (2017), which assess different indicators to rate the value of universities on a global scale, attest to this. In their bid to position themselves in the market and foster lasting relationships with their 'clients' and stakeholders, universities must address the evolution and the realities of the context in which they are operating and adapt to its specific demands. At the same time, they must establish a clear mission (business philosophy), build innovation capacity, achieve sustainability and establish ways to generate value (which will impact on the educational experience of students and have implications for society). Within this context of educational revolution, massive open online courses, or MOOCs, are the latest development in distance learning (Zhou 2016), thanks to their global reach. As a result, they constitute an interesting area of study for the education sector in general, and higher education in particular (Pérez-Sanagustín et al. 2017; Xing 2018; Pursel et al. 2016; García-Martínez et al. 2019).

In a relatively short period of time, millions of people have signed up to MOOCs, which are contributing the democratization of access to university education. If e-learning is the emerging paradigm in modern education (Sun et al. 2008), the growing popularity of MOOCs has led several scholars to consider them a disruptive technology that may threaten the traditional role of universities (Yuan and Powell 2013; Riehemann et al. 2018; Tang et al. 2018). However, as with all new technologies, MOOCs present both advantages and drawbacks (Huang et al. 2017; Reich and Ruipérez-Valiente 2019).

Open education is a tool for social change that requires educational practices at all levels to be reviewed, highlighting the role of the institution in the community and the world (Inamorato dos Santos and Castaño-Muñoz 2016). In this regard, Conole (2016) notes that the heated debate over the value and importance of MOOCs as a disruptive technology falls into two main camps: those who believe in its advantages of access to education and social inclusion; and those who believe that this approach to learning is a mere marketing exercise, whereby MOOCs are designed with the sole purpose of converting their participants into paying undergraduates of the institution. The author further points to the high rate of drop-out from MOOCs.

The economic and financial aspects of MOOCs are further challenges to be addressed (Daniel et al. 2015). In recent years, digital (online) firms have transformed their products and services to offer free access to content that previously carried a cost for the user. Among the more prominent examples are the popular and successful Google Search (universal search system), Wikipedia (digital encyclopedia) and Spotify (music downloads). In the educational realm (and particularly in Higher Education), the innovative teaching–learning model of the MOOC is of particular note, with its differentiating feature of free, open access (Teo et al. 2019). This model is experiencing significant growth and, beyond the participants themselves, is attracting interest also from researchers and professionals from the education sector. Many recognize the unprecedented potential of this format to enable education to reach all corners of the world (Liyanagunawardena et al. 2013).

Precisely, design of effective and attractive learning environments requires knowledge of the factors influencing student learning and perceptions. In this sense, the objective of this research will be to determine the factors that affect the intended use of MOOCs and that have been included in the main theories that underlie the adoption of new technologies or information systems and that have been addressed by the scientific literature in recent years. In this sense, the present study provides a holistic model approaching three of the most significant classical theories such as the technology acceptance model, the self determination theory and SERVQUAL, enhanced with an in-depth analysis of emotions, vividness of content, entertainment and satisfaction.

The structure of this paper is as follows. First, we present a review of the underlying theories, followed by a series of hypotheses drawn from the related literature. Next, we introduce the research method, detailing the participant profile, the research context, and the instrument for data collection and analysis. The findings are discussed, along with the presentation of the structural model. Finally, we discuss and compare the key findings with the extant literature and draw implications for future research.

Literature review and hypotheses

Models and theories: behavior, technology acceptance and learning

According to Song et al. (2017), in general, scholars use a variety of models based on intention as a theoretical framework to analyze attitudes, intentions, acceptance and adoption among users. Among such frameworks are the theory of planned behavior (TPB), the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT). These three are some of the most widely used models in the limited research that has been undertaken on user intention to adopt the distance learning model via MOOCs. Originating from the theory of reasoned action (TRA), they all explain human behavior from socio-psychological perspectives, and each presents different advantages when applied to the study of distance learning.

The TPB is based on three determinants that are conceptually independent of intention: attitude toward a behavior (which is the extent to which a person presents a favorable or unfavorable evaluation of a given conduct); the social factor (subjective norm), which refers to the social pressure perceived by the individual to perform a given behavior or not; and perceived behavioral control, which alludes to the perceived ease or difficulty of carrying out the behavior in question, based on a combination of past experience, impediments and predicted obstacles (Ajzen 1991). As this theory assumes intention to be a predictor of a person's behavior, many authors use it as a basis for studying user intention to adopt educational innovations. Zhou (2016), for example, adopts the TPB to analyze the determining factors of students' intention to use MOOCs, combined with Self-Determination Theory (SDT). Mikalef et al. (2016) also use TPB, in combination with the UTAUT and social cognitive theory or SCT, to examine behavioral intention of students to use video-based learning.

Meanwhile, the TAM is one of the most popular frameworks for exploring technology adoption in different contexts, as noted by Song et al. (2017), and is widely used in hypotheses and conceptual frameworks in research dealing with MOOCs. The TAM holds that an individual's behavioral intention to use a system determines their real use of the technology and is shaped by two beliefs: perceived usefulness (the degree to which the person believes the system in question will improve their performance) and ease of use (the degree to which they believe that using the system will be effortless) (Venkatesh and Davis 2000). Much of the literature reviewed for the present study considers the TAM to be fundamental, whether in its original format, its improved versions (TAM2 and TAM3) or with more variables included to enhance its explanatory power—such as in the works of Wojciechowski and Cellary (2013), Castaño et al. (2015), Mohammadi (2015), Xu (2015) and Pappas et al. (2017). Other authors have used the TAM as the basis for new concepts, such as the web acceptance model (WAM), which predicts user intentions to revisit a website in terms of the moderating effects of Internet experience and website experience (Castañeda et al. 2007). Another notable example of this kind is the personal learning environments (PLE) 2.0 acceptance model. Its results to date suggest that it has adequate predictive power in the study of future use intention for personal learning based on Web 2.0 tools (Del Barrio et al. 2015). In this latter work, satisfaction with e-learning is a determining factor in use intention. As found by Sun et al. (2008), the TAM is appropriate for predicting satisfaction with online learning.

According to Song et al. (2017), the UTAUT is the most suitable theory for studying MOOC adoption when testing several contextual, objective factors. The UTAUT is an extended version of the TAM and is based on four constructs (performance expectancy; effort expectancy; social influence; and facilitating conditions) and four moderating variables (gender, age, experience of technology and voluntariness of use). The model thus explains a higher percentage of variance in behavioral intention. The video-based learning (VBL) conceptual model developed by Mikalef et al. (2016) is based on the UTAUT. The VBL model holds that individuals' cognitions, perceptions and predispositions toward a specific medium can determine its success or failure in terms of adoption.

In addition to these three main theories, there are other behavioral models used in various studies to analyze use intention for e-learning and MOOCs. These include: Self-determination Theory, which was included in the work of Roca and Gagné (2008) and Zhou (2016); the expectation–confirmation model (ECM), used in the works of Thong et al. (2006), Sun et al. (2008), Lee (2010) and Alraimi et al. (2015); the grounded theory method (GTM), which was adopted by Adamopoulos (2013) to study the real educational needs of MOOC students and their satisfaction; expectation disconfirmation theory (EDT), which provided the basis for the study by Shahijan et al. (2016) to analyze the factors that influence satisfaction and continuance intention; regulatory focus theory (RFT), which was applied in the work of Zhang (2016); social cognitive theory (SCT), used by Mikalef et al. (2016); and task-technology fit theory, which was included in the research of Huang et al. (2017).

Turning to pedagogical models, among the most notable studies in our review are those of Castaño et al. (2015) and Wojciechowski and Cellary (2013). The former work supports the use of MOOCs as part of a collaborative pedagogical design, while the latter adopts a constructivist pedagogical approach that encourages students to be active learners that make their own discoveries and arrive at their own conclusions. Del Barrio et al. (2015) examine social constructivism as a pedagogical model used in personal learning environments, which provides greater flexibility in the use of digital technology applied to education, as it focuses on the personal needs of students. In this regard, according to the findings of Magen-Nagar and Cohen (2017), learning strategies constitute a significant mediator between the motivation and academic achievement of MOOC students, who engage with the course independently. The social pedagogy model supports the socio-cognitive aspects of students while improving and promoting strategies that are suited to their needs.

Given the context in which distance learning is developing, and the present literature review, in the following sections we set out the dimensions under consideration to explain MOOC use intention. The dimensions are: ease of use; vividness of content; interactivity; controlled motivation; autonomous motivation; entertainment; course quality; usefulness; emotions; and satisfaction.

Effect of perceived ease of use

Of all the constructs used in the present study to explain MOOC use intention, perceived ease of use and perceived usefulness are the two most commonly applied in the literature. As highlighted by Mohammadi (2015), in the case of the TAM, ease of use refers to the user's perception of the extent to which the use (adoption) of a given system is likely to be effortless, this being a determining factor in the acceptance of new technological applications. There is extensive empirical evidence of a significant relationship between perceived ease of use and intention–both directly, and indirectly via its impact on perceived usefulness (Venkatesh and Davis 2000).

If students believe that e-learning is likely to be easy to use, they are more likely to accept the system positively and continue to use it (Lee et al. 2009), as they will regard the system as being both simple and satisfactory (Sun et al. 2008). Therefore, according to Cigdem and Ozturk (2016), it is also likely that users will join in, use the system more and spend longer on it. Furthermore, the direct influence of ease of use on perceived usefulness may encourage users to consider the system beneficial and functional—a factor that system administrators should take into account, to design learning platforms that are easy to use and that facilitate learning. Huanhuan and Xu (2015) demonstrated the positive effect of perceived ease of use and interaction on MOOC use intention. Taking these two factors into account, the authors measured the degree to which the platform was easy to handle—that is, whether the user was prepared to participate and complete the course, and whether they perceived the importance of interactive learning.

Overall, the findings of Lee (2010), Wojciechowski and Cellary (2013), Del Barrio et al. (2015) and Xu (2015) corroborate the positive relationship between ease of use and usefulness, and the direct or indirect relationship between ease of use and intention to use distance learning technologies (acceptance or continuance).

Based on these theoretical assumptions and the empirical findings from the aforementioned works, the following research hypotheses are proposed:

H1 Perceived ease of use exerts a positive influence on perceived usefulness among MOOC users.

H2 Perceived ease of use exerts a positive influence on MOOC use intention.

Effect of vividness of content

Vividness of content is a factor typically mentioned in the literature on web-based environments and technologies, but rarely associated with MOOC use intention. In their research on the effects of interactivity and vividness of message on attitudes and behavioral intentions in online advertising, Fortin and Dholakia (2005) refer to vividness of the message (also known as media richness) in terms of two fundamental concepts: breadth (the number of sensory dimensions, signals and senses presented) and depth (quality and resolution of presentation). According to these authors, vividness is often confused with interactivity, but the two differ in their capacity for two-way communication. In other words, the means of communication may be vivid but not interactive (such as television) or vice versa (such as email). Following this logic, the inclusion of both concepts in the present study is justified by the bidirectional nature of the MOOC learning environment. Furthermore, as these authors affirm, the vividness of service-provision platforms can help professionals, managers and researchers to determine their suitability for achieving a given objective.

To measure vividness of MOOC content, the present study used the scale developed by Huang et al. (2017). These authors took vividness to refer to the degree to which the presentation of the course is valuable and attractive to students. In addition, in contrast to traditional learning settings, given that distance learning students cannot interact directly or instantaneously with teachers, the question of interactivity may prove to be a determining factor in MOOC use intention. The following hypothesis is therefore proposed:

H3 Vividness of content exerts a positive influence on MOOC use intention.

Effect of perceived interactivity

As we saw earlier, Fortin and Dholakia (2005) hold that there can be confusion between the concept of vividness and that of interactivity. According to these authors, interactivity refers to the degree to which a system allows users to act as both senders and receivers of a communication, be it in real time or asynchronously, and to search for (and access) information in such a way that the content, timing and sequence of the communication are controlled by them.

In virtual learning environments, interaction during activities (between students, with the teachers and with the learning materials) can contribute to problem-solving and improve learning effects (Sun et al. 2008). This positive influence of interaction is magnified further in the case of MOOCs, which attract great diversity among students (different ages, nationalities, skill-levels, interests and so on). Given that the capacity to learn, interact and collaborate on a MOOC can be realized at local, international and global level (from any location and at any time of day), one of the main concerns among the educational community is the limited interaction that MOOCs offer between teachers and learners (Brahimi and Sarirete 2015). Cigdem and Ozturk (2016) find that interactivity is a major feature of all contemporary learning environments, which can be improved by means of appropriate technologies and pedagogical approaches. According to previous studies, the degree of interactivity provided by an LMS platform influences its use and may represent a significant dimension that determines students' adoption or rejection of the system.

To measure the perceived interactivity of MOOCs, the present study used the scale developed by Huang et al. (2017), who conceptualized (functional) interactivity as the degree to which a MOOC includes features that enable greater interaction between teachers and learners. Given that, in a MOOC, students watch recorded lectures on video, interaction plays a fundamental role, particularly in the case of more complex courses. In view of these factors, the following hypothesis is submitted:

H4 Perceived interactivity exerts a positive influence on MOOC use intention.

Effect of controlled motivation

The term *motivation* derives from the notion of *movement*, referring to the impulses and instincts that lead a person to take action. Scholars developed a differentiation between intrinsic and extrinsic motivation as a central factor in all discourse on the subject (Magen-Nagar and Cohen 2017). Of the works covered in our literature review, those that include analysis of motivation typically develop their propositions on the basis of SDT or TPB.

Zhou (2016) explains that SDT distinguishes between *autonomous* and *controlled* motivations, in terms of their underlying regulating processes and their associated degrees of self-determination. According to this author, autonomous motivation predicts continuance intentions, while controlled motivation diminishes the intention to become involved in a given behavior. The literature also describes external motivations as controlled motivations. Meanwhile, Lee (2010) contends that the TPB should be included in the model of e-learning adoption, as users have to deal with several limitations, such as the impersonal nature of the online setting, the need for certain resources and skills (perceived behavioral control) and the influence of normative opinions or beliefs stemming from others' expectations (subjective norms). According to the results of Lee (2010), both subjective norms and perceived behavioral control have a significant influence on continuance intention. This indicates that if others in the student's environment have already adopted a given e-learning system, he or she will be more likely to do so.

In the present work, controlled motivation was measured on the scale developed by Zhou (2016). This author takes controlled motivation to be, by its very nature, the opposite of autonomous motivation, referring to the external incentives that drive human behavior. Although the aim of her work was also based on analyzing the factors that influence intention among MOOC students, it dealt with the indirect relationships with continuance intention (via perceived behavioral control, attitude and subjective norms) among users with previous experience of this type of course.

With this in mind, the following research hypothesis is proposed:

H5 Controlled motivation exerts a positive influence on MOOC use intention.

Effect of autonomous motivation

Continuing with Zhou's (2016) distinction between types of motivation, the literature suggests that behavior can be characterized as self-determined or not self-determined, depending on the extent to which it is triggered by autonomous or controlled stimuli. According to the literature, motivations that are identified, integrated and intrinsic are autonomous, and are generally more influential than controlled motivations. In this regard, in SDT, intrinsic motivation refers to the performance of an activity for the good of the individual (derived from their interest in the task itself), while extrinsic motivation refers to the performance of a task to achieve something that is distinct from the task or is for a purpose beyond the task itself (such as to gain some kind of recompense or reward, or to avoid punishment) (Xiong et al. 2015).

This theory holds that human beings have a basic psychological need for autonomy, competence and relatedness. Studies on SDT suggest that people are more likely to persist and perform better in those tasks that satisfy these needs (Roca and Gagné 2008). According to various other studies (Alraimi et al. 2015; Huanhuan and Xu 2015), individual motivation includes intrinsic motivation (personal satisfaction) and extrinsic motivation (derived from achieving the desired outcome). Intrinsic motivation is typically measured in terms of interest, satisfaction, enjoyment and commitment, while extrinsic motivation is measured in terms of self-development, reputation and perceived usefulness. In the educational context of MOOCs, students may bring both intrinsic and extrinsic motivation—that is, curiosity and a thirst for new experiences, on the one hand, and the need to obtain new skills or credentials that will be of benefit to them in the future, on the other. According to the findings of the aforementioned authors, motivation (in both its forms) is a significant predictor of the learner's commitment to the course, which, in turn, is a major predictor of retention on the MOOC.

As Zhou (2016) considers the autonomy dimension to be the opposite of the control dimension, the present study uses this author's scale to measure autonomous motivation (understood as the inner incentives that drive human behavior). As with controlled motivation, in view of the scarcity of specific previous works on the topic, the present study proposes an alternative to the work of Zhou. By contrast to her approach, the sample population includes both students with some experience in the use of MOOCs and those with none and includes a direct relationship between autonomous motivation and use intention.

On this premise, the following hypothesis is proposed:

H6 Autonomous motivation exerts a positive influence on MOOC use intention.

Effect of perceived entertainment

According to Zhang (2016), there is a generalized belief in the role of entertainment (fun or enjoyment) as a significant dimension that influences a person's intention to do something. The author confirms this belief with results from her study on intention to learn via a MOOC. Elsewhere, of the courses examined in the study conducted by Kizilcec et al. (2013), the two main motives that were found to explain why students enrolled were fun/challenge and interest in the subject. Wojciechowski and Cellary (2013) corroborated the positive relationship between perceived enjoyment and intention to use augmented reality learning environments, enjoyment being an even more significant factor than perceived usefulness. Therefore, while some learning contexts may present characteristics that are particularly favorable to user perceived entertainment, this variable may have an important role in use intention for Web technologies and MOOCs. In this context, Yuan and Powell (2013) found that one of the aspects of MOOCs that motivated learners to participate was the pleasant social experience it offered (alongside the acquisition of knowledge and skills). Lee (2010) also found that perceived enjoyment (understood as the extent to which the use of a system is perceived as pleasant, regardless of the performance outcomes derived from its use) influenced attitudes among students, who not only wanted to learn on the course but also communicate with other participants.

Elsewhere, other studies specifically propose a relationship between perceived enjoyment or entertainment and user satisfaction (Thong et al. 2006; Qin and Xu 2007; Alraimi et al. 2015). As people use some technologies for entertainment purposes, the expectation of a pleasant experience while using such technologies could constitute a key factor in user satisfaction (Thong et al. 2006). In view of these aspects, the following hypotheses on entertainment are proposed:

H7 Perceived entertainment exerts a positive influence on MOOC use intention.

H8 Perceived entertainment exerts a positive influence on MOOC user perceived satisfaction.

Effect of perceived course quality

The quest for consensus on the definition of quality has led to several different propositions, based on concepts such as value, compliance (with specifications or requirements) or exceeding user expectations. Camilleri et al. (2014) assert that quality is an amorphous concept rather than an objective entity. Hence, they propose a conceptual map of the notion of quality that can be associated with the context of open educational resources. On this basis, they examine the confluence of five concepts: efficacy or fitness-for-purpose of the object or concept being evaluated (such as the ease of re-use or educational value); impact, which is the degree to which an object or concept proves effective (and which depends on the nature of that concept); availability (in the sense of transparency or ease of access), which is a prerequisite of efficacy and impact; accuracy, which refers to both precision and the absence of errors; and excellence, which compares the quality of an object or concept with its peers and against its own potential for quality. According to Inamorato dos Santos and Castaño-Muñoz (2016), quality can be understood as the convergence between these five concepts and an institution's open learning offer and opportunities. Conole (2016) regards e-learning quality as the extent to which it can be considered a good learning experience, on the basis of excellence and value.

In the study by Daniel et al. (2015) on the future of MOOCs, they analyze the key dimensions that such courses should address if they are to make significant progress in terms of quality and effectiveness in their contribution to Higher Education. These dimensions are: the teaching model; monetization processes; certification; adaptive learning; and implementation of MOOCs in developing countries. According to the findings of Mohapatra and Mohanty (2016), the quality of content and the reputation of the educators and universities associated with MOOCs are particularly important factors for students. On this point, Aguaded and Medina-Salguero (2015) highlight the generalized interest in assessing educational quality, pointing to the appearance of different national and international bodies established for that purpose. The European Foundation for Quality in E-learning (EFQUEL) is one such example of an organization designed to promote innovation and excellence in education. Among its initiatives was the MOOC Quality Project, devoted to stimulating debate on the quality of this educational approach.

Mora (2011) notes that the marketing literature reflects major scholarly interest in the relationship between quality and satisfaction. This is mainly due to the fact that perceptions of quality and judgments about satisfaction are key constructs for understanding consumer behavior. For example, the research conducted by Román et al. (2014) corroborates that service quality in the online environment generally has a positive effect on satisfaction levels. In view of the focus on the relationship between these constructs in different settings (both virtual and classroom-based), the effect of quality on satisfaction in the distance learning context requires examination.

Quality, being multidimensional, needs to be observed from various perspectives. Among these, the opinion of the learners themselves can be considered the most important, as they are the direct participants in the higher education system (Puska et al. 2016). These authors assert that the job of a quality system is not only to meet legal requirements, but also to contribute to generating student satisfaction (which will translate into loyalty). Given the complexity of the quality construct and the difficulty of operationalizing many of its dimensions, there is no single, universally accepted approach to measuring it (Hood and Littlejohn 2016). To analyze the relationship between quality of e-learning courses and student satisfaction, Udo et al. (2011) proposed a modified version of the SERVQUAL instrument, based on five dimensions (assurance, empathy, responsiveness, reliability and website content). All of these dimensions, with the exception of reliability, were found to play a significant role in perceived e-learning quality, which also affects student satisfaction.

To measure the quality of MOOCs, the present study uses an adapted version of the scale originally developed by Sun et al. (2008), who considered e-learning quality to be a significant factor in online student satisfaction. On this basis, the following hypothesis is proposed:

H9 Perceived course quality exerts a positive influence on users' perceived satisfaction with MOOCs.

Effect of perceived usefulness

We have seen that perceived ease of use and perceived usefulness are two of the factors most commonly employed in the literature to analyze technology use intention—one of the reasons being that they form part of the TAM, which is among the most popular models for research on distance learning. According to Sun et al. (2008), who apply the TAM to e-learning, the greater the perceived usefulness and ease of use of websites offering courses and of file-transfer systems, the more positive students' attitudes to this type of learning. These authors define perceived usefulness as the degree of improvement in learning effects due to the adoption of a given e-learning system.

The present literature review identified various studies that provide empirical support for the relationship between usefulness and satisfaction in the contexts of information technology use and e-learning—for example, Thong et al. (2006), Qin and Xu (2007), Lee (2010) and Cigdem and Ozturk (2016). The personal learning environments acceptance model (PLE 2.0) proposed by Del Barrio et al. (2015) holds that student satisfaction is influenced by their perceptions of the usefulness of a given system, particularly among those users with a high need for cognition.

Numerous other studies provide empirical support for the positive influence of perceived usefulness on use intention, applied to various spheres of study and technologies (Huanhuan and Xu 2015; Pappas et al. 2017; Ma and Lee 2019).

In the latter study, Pappas et al. also demonstrated the relationship between perceived usefulness—referring to the extent to which learners believe that video-based tasks will improve their performance—and emotions (based on entertainment or interest). The argument posited by these authors is that this learning system can offer major benefits to students, such as access to the course materials at any time and from any location, and the freedom to study at their own pace. Therefore, it is to be expected that such benefits will heighten use intention and trigger positive emotions, such as enjoyment and excitement. When learners are able to understand the positive consequences of using this system in particular, they are more likely to enjoy it.

In light of these considerations, the following research hypotheses are proposed:

H10 User perceived usefulness of MOOCs exerts a positive influence on user perceived satisfaction with MOOCs.

H11 User perceived usefulness of MOOCs exerts a positive influence on MOOC use intention.

H12 User perceived usefulness of MOOCs exerts a positive influence on user emotions.

Effect of emotions

Emotions constitute a major dimension of technology acceptance, and can influence user behavioral intention (Beaudry and Pinsonneault 2010). Given the gap in the empirical research on emotions and the call for investigation into the emotions of students (Thong et al. 2006; Alraimi et al. 2015; Pappas et al. 2017), this factor is included in the present study in relation to its possible influence on MOOC use intention.

According to Kay and Loverock (2008), due to the increased presence of computers in modern life, it is of no surprise that users at times express emotional reactions including rage, desperation, anxiety or relief. It is also logical to believe that emotions play a part in the process of learning via computers. These authors sustain that the full range of emotions should be studied (not only levels of anxiety, for instance), as even though users may experience some emotions in private (or not express them openly), anger, happiness and sadness also form part of the learning process.

Rienties and Rivers (2014) find that emotions play a critical role in the teaching and learning process, as they exert an influence on motivation, self-regulation and academic performance among learners. However, the educational research in general has devoted little attention to the study of emotions. These authors suggest that analysis of user behavior could provide a valid approach to measuring and understanding emotions, which can arise at any point in the learning process and may be completely different—or completely the opposite—for different students.

In light of these reflections, the following research hypothesis is proposed:

H13 Users' emotions exert a positive influence on MOOC use intention.

Effect of satisfaction

As Ruiz et al. (2010) affirm, just as in the case of studies on consumer behavior, satisfaction is a topic of great interest to professionals from different fields. One of the reasons for this interest is that the variables typically associated with satisfaction have a major impact on business profitability and growth—such as loyalty, competition, costs or reputation. Perceived satisfaction tends to be used to assess the success or failure of a system (Cigdem and Ozturk 2016), particularly in the case of continuance intention, as use of the system precedes user satisfaction (Mohammadi 2015). Thus, there is also a wide variety of studies that provide empirical backing for the direct effect of satisfaction on use intention for a technology applied to learning contexts. Such studies include those of Thong et al. (2006), Lee (2010), Udo et al. (2011), Alraimi et al. (2015), Del Barrio et al. (2015), Shahijan et al. (2016) and Hyo-Jeong So and Kim (2018).

Not only has satisfaction been shown to be one of the most significant concepts in the marketing literature to be applied to the online education context (Alraimi et al. 2015); it has also been found to have the most significant influence on user continuance intention, followed by perceived usefulness (Lee 2010). Satisfaction also acts as a mediator between perceived e-learning quality and user behavioral intention (Udo et al. 2011; Ayala et al. 2014).

In view of these considerations, the following hypothesis is proposed:

H14 User perceived satisfaction exerts a positive influence on MOOC user intention.

Drawing on the previous literature discussed in the preceding sections, we propose the following research model (see Fig. 1).

Methodology

Measurement scales

The measurement instrument employed in the present study to collect data was an online questionnaire adapted to the context of MOOCs. It was designed around the measurement scales developed, adapted and validated by other authors in earlier studies. The scales measuring perceived ease of use, course quality and satisfaction were taken from the work of Sun et al. (2008) and adapted accordingly. The scales for perceived usefulness and entertainment were adapted from the measurement instruments devised by Alraimi et al. (2015). The emotions and use-intention scales were adapted from the recent work of Pappas et al. (2017). Vividness of content and perceived interactivity were measured on scales adapted from those of Huang et al. (2017). And controlled motivation and autonomous motivation were measured on

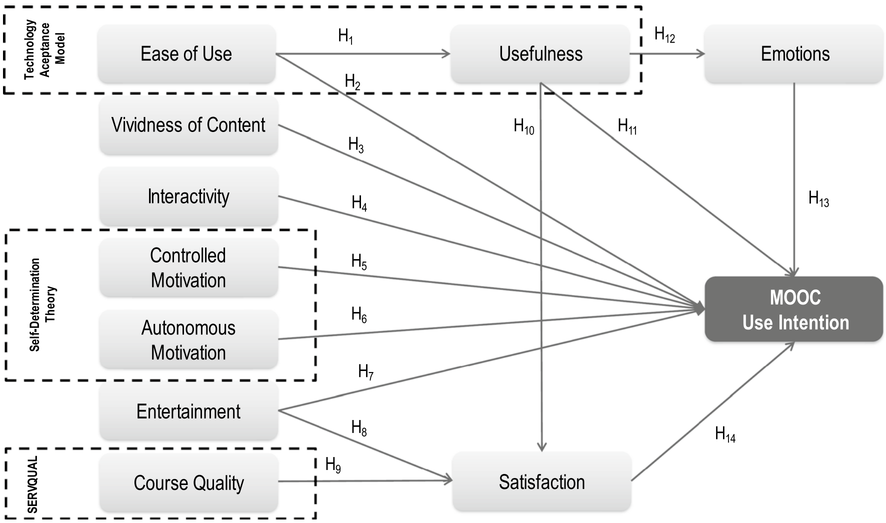

Fig. 1 Hypotheses and research model

scales based on the work of Zhou (2016). Further detail on the scales and items used in the questionnaire can be found in the "Appendix".

The questionnaire was divided into three distinct parts. The first part was an introduction, welcoming participants to the study. This provided the information necessary for them to register their responses correctly. It also provided some background context for participants, comprising a brief written explanation of MOOCs and a 1-min introductory video. The second part set out the full list of questions, based on the items or propositions (translated into Spanish) that participants were being asked to score. For this purpose, a seven-point Likert scale was used (where 1 = entirely disagree and 7 = entirely agree). Questions were grouped in line with each of the 11 constructs being measured. The third and final part of the questionnaire consisted of questions designed to elicit sociodemographic data about the participants, for possible future comparative analysis. These questions covered: gender, age, nationality, educational level, employment status, level of English proficiency, level of Internet and social media use, and previous knowledge and experience of online learning.

Sample design and data-collection

The primary data used for testing the hypotheses were gathered by means of the self-administered questionnaire. Given the overarching aim of the research—to identify the factors that determine MOOC use intention—the characteristics of the target population presented certain generic requirements related to the highly diverse profile typical of this type of course participant. These included being at least 16 years of age and of different nationalities, being Spanish-speaking (sufficiently to respond to the questionnaire) and with knowledge of the Internet and social networks (see Table 1).

Table 1 Technical specification and sample characteristics

Population	Spanish-speaking Internet users over 16 years of age
Sample type	Non-probabilistic (convenience)
Sample size	210 valid cases
Period of fieldwork	June–July 2017

Respondents saw a video explaining how MOOCs work. After watching it, participants were asked to complete an online questionnaire.

Before entering the survey website, users were expressly informed that they had to remember a promotional code (No. 218) that appeared at the end of the video to make sure they saw the full video. We only used the data for our study of users who could correctly remember the code. According to various studies (Wells 1997; Liébana-Cabanillas et al. 2018) any information that is processed either consciously or unconsciously activates the memory, which could increase the likelihood of the participants remembering the messages they were shown, which would therefore guarantee greater reliability of the achieved results. According to Hu et al. (2010), we saw to it that participants followed instructions and did not consider questionnaires that were completed in too long a time (Ray et al. 2011).

A total of 212 questionnaires were collected, two of which were discounted due to errors in the responses, leaving 210 valid cases. Table 2 shows the profile data for the sample under study.

Results

Structural equation modeling (SEM) was used to fulfill the research aims. This approach was selected on the basis that, as Hair et al. (2010) indicated, it enables the measurement model and the structural model to be differentiated. By means of this multivariate analysis technique, different (interdependent) multiple regression equations are combined simultaneously. SEM is widely used in marketing research and in the social sciences in general (Del Barrio and Luque 2012).

To manage the data, first the necessary statistical checks were conducted. Once validity was confirmed, a confirmatory factor analysis (CFA) was carried out, using *SPSS Statistics 21.0*. Lastly, empirical validation of the proposed theoretical model was achieved by means of the SEM technique, using *SPSS Amos 23.0* software.

The next sections explain the process followed in each step, together with the results. Finally, the proposed hypotheses are tested.

Table 2 Profile of the sample population

Sociodemographic indicator	*N*	%
Gender		
Male	87	41.4
Female	123	58.6
Age		
16–24 years	20	9.5
25–34 years	51	24.3
35–44 years	64	30.5
45–54 years	45	21.4
55–64 years	25	11.9
≥ 65 years	5	2.4
Nationality		
Spanish	183	87.1
Other	27	12.9
Educational level		
Primary	18	8.6
Secondary	53	25.2
University degree	80	38.1
University postgraduate degree	59	28.1
Employment status		
Unemployed	26	12.4
Full-time employment	99	47.1
Part-time employment	26	12.4
Student	14	6.7
Combines work with study	28	13.3
Retired or semi-retired	11	5.2
Does not work for other reasons	5	2.4
Runs own business	1	0.5
Have you ever studied on an e-learning course (non-MOOC)?		
Yes	131	62.4
No	79	37.6

Data analysis

Statistical description of the sample

Statistical checks were conducted on the sample under analysis to establish the validity of the methodological assumptions. The resulting values are shown in Table 3.

The most highly scored items were those relating to usefulness and interactivity, together with the majority of those referring to ease of use. Those items attracting the lowest scores were those associated with controlled motivation, and two items referring to satisfaction. The variables presenting the greatest deviation of data were controlled motivation and use intention, along with some

Table 3 Descriptive data and skewness and kurtosis tests

Construct	Variable	Mean	SD	Skewness	Kurtosis
Perceived ease of use	PEU1	5.55	1.19	– 4.50	1.76
	PEU2	5.58	1.18	– 4.67	1.98
	PEU3	4.83	1.33	– 1.00	– 0.83
	PEU4	5.65	1.26	– 4.76	0.52
Perceived usefulness	PU1	5.55	1.31	– 5.12	1.54
	PU2	5.56	1.26	– 3.64	– 0.74
	PU3	5.61	1.30	– 3.81	– 1.05
Emotions	EM1	5.45	1.21	– 4.61	2.36
	EM2	4.98	1.55	– 3.72	– 0.40
	EM3	5.10	1.44	– 3.14	– 1.05
Vividness of content	VC1	5.41	1.17	– 3.68	1.09
	VC2	5.27	1.20	– 2.76	0.02
	VC3	5.05	1.35	– 3.04	– 0.21
	VC4	5.14	1.30	– 3.29	0.66
Perceived interactivity	PI1	5.47	1.35	– 4.37	– 0.16
	PI2	5.57	1.29	– 4.76	0.51
	PI3	5.65	1.26	– 5.22	1.19
	PI4	5.67	1.24	– 5.45	1.95
Controlled motivation	CM1	4.55	1.68	– 2.05	– 1.90
	CM2	2.85	1.76	3.67	– 2.05
	CM3	3.84	1.87	0.16	– 2.97
	CM4	2.50	1.92	6.51	– 0.07
Autonomous motivation	AM1	5.00	1.61	– 3.04	– 1.26
	AM2	5.34	1.32	– 3.25	– 0.63
	AM3	5.36	1.42	– 4.12	– 0.39
	AM4	4.88	1.46	– 1.47	– 1.52
	AM5	4.93	1.43	– 2.37	– 1.17
Perceived entertainment	PE1	5.19	1.34	– 2.87	– 0.40
	PE2	4.96	1.38	– 2.43	– 1.50
	PE3	5.02	1.42	– 2.44	– 1.87
Perceived course quality	PCQ1	5.06	1.36	– 2.22	– 1.05
	PCQ2	4.97	1.37	– 2.81	– 0.37
	PCQ3	4.95	1.54	– 3.12	– 0.57
Perceived satisfaction	PS1	5.50	1.24	– 3.71	– 0.49
	PS2	5.43	1.42	– 3.39	– 1.25
	PS3	5.30	1.35	– 3.08	– 1.02
	PS4	5.09	1.41	– 2.88	– 0.66
	PS5	4.57	1.62	– 2.36	– 1.44
	PS6	2.99	1.72	3.89	– 1.78
	PS7	3.41	1.86	1.54	– 3.02

Table 3 (continued)

Construct	Variable	Mean	SD	Skewness	Kurtosis
Use intention	UI1	5.13	1.63	– 3.74	– 0.75
	UI2	4.98	1.67	– 3.52	– 1.34
	UI3	4.67	1.66	– 2.30	– 1.82
	UI4	5.23	1.54	– 3.65	– 1.22
	Multivariate	Mardia's coeff: 368.43; *CR* 41.96			

of the satisfaction items. By contrast, the variables with the lowest standard deviation were ease of use, vividness of content and interactivity.

Analysis of multivariate normal distribution

Prior to analyzing any model, the requirements established in the literature for correctly applying the aforementioned techniques need to be checked: that the relationships between the variables are linear; that the model is identified; and that the data follow a normal distribution. As noted by Del Barrio and Luque (2012), a model is identified if the input matrix (correlations or variances–covariances) of the variables under observation is generated only by one set of parameters. In this case, the proposed model is recursive—that is, the errors are not related, and all the causal effects are unidirectional. The present model was thus confirmed to be identified.

With regard to the hypothesis of normality across the data, this was verified by analyzing the asymmetry and kurtosis of the variables.

As Table 3 shows, the majority of the critical ratio (CR) values for asymmetry and some of the kurtosis values were outside the ± 1.96 interval. The majority of the variables were therefore considered not to follow a normal multivariate distribution. The kurtosis value from Mardia's test also showed that these variables did not jointly follow a normal distribution (CR 41.96).

Therefore, following the recommendations of the literature (Del Barrio and Luque 2012) on making the appropriate transformations to bring the variables closer to multinormality, the maximum likelihood method of model estimation was used, together with resampling or bootstrapping (based on 500 samples). An appropriate reference for such cases is the Bollen–Stine corrected *p* value (with a confidence interval of 95%).

It is important to reiterate that the scales used in the present study were previously validated by other authors. For this reason, as well as the subsequent verification of the existence of discriminant validity between the latent constructs (explained in the next section), it was decided that the issue of possible errors of multicollinearity could be disregarded.

Overall fit of the model

The overall fit provides a joint analysis of the measurement model and the structural model, to check the correspondence between the matrix reproduced by the model and that of the observed data (Del Barrio and Luque 2012). In this case, the absolute and incremental measurements were verified. Given the sample size of the study, the fit indices values were close to those recommended in the literature (as can be observed in Table 4) (Sivo et al. 2006). The RMSEA indicated that the model presented an adequate overall fit. Following Del Barrio and Luque (2012), the RGAFI indicator was used as another adequate measure to evaluate the model, being above the recommended value (0.8). These values did not include those for items PS6 and PS7, as it was shown that the loads did not reach the minimum level recommended by the literature.

Evaluation of the measurement model

The psychometric properties of the scales used in the investigation were analyzed by means of confirmatory factor analysis (CFA). The relationship between the observed and latent variables under analysis were measured via their consequences. This was therefore a reflective measurement (common in CFA applied in marketing-related research). Thus, the relationships that flowed from the unobserved variables toward its indicators (manifest variables) were identified.

In this stage of evaluating the model, the aim was to test whether the scales used were valid (if they measured what they were meant to measure) and reliable (their degree of accuracy).

In the present study, convergent validity was checked using the magnitude of the factor loads of the indicators. Fornell and Larcker (1981) recommend that three conditions be taken into account to assess convergent validity of scale items: all factor loads should be significant and over 0.70; composite reliability for each construct should exceed 0.70; and average variance extracted (AVE) should be over 0.50.

The results (see Table 5) show that the loads were significantly different from zero (with the exception of PS7) and over 0.70 (except for CM4, PS6 and

Table 4 Fit indices of the model *Source:* Own elaboration, based on Del Barrio and Luque (2012)

	Indicator	Value obtained	Recommended value
Absolute fit indices	Normed Chi squared	2.37	> 2 and < 5
	RAGFI	0.803	> 0.80
	Root mean square error of approximation (RMSEA)	0.08	< 0.08
Incremental fit indices	Incremental fit index (IFI)	0.88	≥ 0.90
	Non-normed fit index or Tucker–Lewis index (NNFI/TLI)	0.87	> 0.90
	Comparative fit index (CFI)	0.88	≥ 0.90

Table 5 Convergent validity and reliability indicators

Construct	Standardized coefficient (SE)	Cronbach's α	CR	AVE
Perceived ease of use				
PEU1	0.86	0.89	0.90	0.69
PEU2	0.94			
PEU3	0.65			
PEU4	0.85			
Perceived usefulness				
PU1	0.87	0.91	0.91	0.77
PU2	0.89			
PU3	0.86			
Emotions				
EM1	0.80	0.88	0.88	0.71
EM2	0.87			
EM3	0.87			
Vividness of content				
VC1	0.89	0.93	0.93	0.76
VC2	0.88			
VC3	0.88			
VC4	0.84			
Perceived interactivity				
PI1	0.90	0.93	0.93	0.76
PI2	0.92			
PI3	0.81			
PI4	0.84			
Controlled motivation				
CM1	0.72	0.80	0.80	0.51
CM2	0.67			
CM3	0.89			
CM4	0.54			
Autonomous motivation				
AM1	0.85	0.93	0.93	0.72
AM2	0.86			
AM3	0.85			
AM4	0.86			
AM5	0.81			
Perceived entertainment				
PE1	0.89	0.94	0.94	0.84
PE2	0.95			
PE3	0.91			
Perceived course quality				
PCQ1	0.77	0.77	0.78	0.55
PCQ2	0.82			
PCQ3	0.62			

Table 5 (continued)

Construct	Standardized coefficient (SE)	Cronbach's α	CR	AVE
Perceived satisfaction				
PS1	0.89	0.94	0.94	0.77
PS2	0.89			
PS3	0.95			
PS4	0.89			
PS5	0.75			
Use intention				
UI1	0.92	0.94	0.94	0.81
UI2	0.91			
UI3	0.92			
UI4	0.84			

PS7). The variance extracted was also above 0.50 in all cases. Therefore, it can be affirmed that the majority of the latent variables adequately explained the observed variables (Del Barrio and Luque 2012).

Considering these values, according to the literature (Hair et al. 2010), if the standardized coefficient of an item is within the interval 0.04–0.70, eliminating that item would affect the validity of the content. It is therefore advisable to analyze the impact on composite reliability and variance extracted. Some of the standardized values for the factor loads were within the aforementioned interval: PEU3 (0.65), CM2 (0.67), CM4 (0.54) and PCQ3 (0.62); but they were also significant. Hence, it was decided that these items should be retained on their respective scales. However, two factors of the "satisfaction" construct were detected as having loads that were not significant (both PS6 and PS7 were well below 0.40). These items were therefore eliminated from the scale.

Turning to reliability, this is analyzed in terms of internal consistency—that is, coherence in the responses to the items that measure a given construct. As well as the aforementioned AVE values, the Cronbach's alpha (α) value and composite reliability (CR) or Jöreskog's rho (ρ) were also taken into account (Fornell and Larcker 1981; Hair et al. 2010; Del Barrio and Luque 2012). All the results from these checks presented values above the accepted limits—that is, above 0.70 for simple and composite reliability, and over 0.05 for variance extracted. The scales used in the present research were therefore verified as reliable.

Discriminant validity, which determines that one construct is different from another, was tested using the confidence interval, setting the variance of the latent variables to 1 in the specification of the model. None of the intervals was found to include 1. Discriminant validity between factors was therefore demonstrated, with each one providing unique information that was not included in any other.

Evaluation of the structural model

According to Hair et al. (2010), structural equation modeling is suitable for verifying the relationships between the constructs of a proposed model. In this phase of the present evaluation, the relationships between the latent constructs were analyzed, to test the hypotheses originally proposed. As mentioned earlier, a reflective measurement model was used (this approach being more commonly used than formative modeling), in which the latent variable causes the indictors.

To assess the structural model and test the research hypotheses, the following aspects were tested: the statistical significance of the structural loads of the relationships proposed in the model; the relative importance of the effects of the exogenous variables on the endogenous variables; and the predictive capacity of the latent endogenous variables using the R^2 or coefficient of determination for each dependent variable (Hair et al. 2010). Table 6 shows that, of the 14 relationships proposed in the model, 8 of the structural loads were significantly different from zero (with a *p* value mainly of between 0.01 and 0.10); the remaining six relationships, however, were not significant.

The most important variables for explaining use intention were found to be satisfaction ($\beta = 0.54$) and autonomous motivation ($\beta = 0.48$), while the variable with the greatest effect on satisfaction was course quality ($\beta = 0.51$). These were all considered to be substantial values (Hair et al. 2010). The influence of usefulness on emotions ($\beta = 0.79$) and ease of use on usefulness ($\beta = 0.66$) can be considered strong effects, as they presented values above 0.60.

Table 6 Summary of results for the research hypotheses

Hypothesis		Standardized β	SE	*p* value	Empirical support
H1	Ease of use ➔ usefulness	0.66	0.07	***	Yes
H2	Ease of use ➔ use intention	0.06	0.11	N.S.	No
H3	Vividness of content ➔ use intention	0.07	0.12	N.S.	No
H4	Interactivity ➔ use intention	– 0.10	0.09	N.S.	No
H5	Controlled motivation ➔ use intention	– 0.02	0.05	N.S.	No
H6	Autonomous motivation ➔ use intention	0.48	0.14	***	Yes
H7	Entertainment ➔ use intention	– 0.10	0.13	N.S.	No
H8	Entertainment ➔ satisfaction	0.22	0.08	**	Yes
H9	Course quality ➔ satisfaction	0.51	0.10	***	Yes
H10	Usefulness ➔ satisfaction	0.38	0.05	***	Yes
H11	Usefulness ➔ use intention	0.01	0.15	N.S.	No
H12	Usefulness ➔ emotions	0.79	0.08	***	Yes
H13	Emotions ➔ use intention	– 0.15	0.10	*	No
H14	Satisfaction ➔ use intention	0.54	0.14	***	Yes

N.S. non-significant

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

With regard to the empirical testing of the hypotheses, in light of these results a series of important considerations arise. These are now discussed.

Hypotheses H1 and H2, relating to ease of use, could not be entirely rejected. In the case of H1, in line with the results of the literature review (Del Barrio et al. 2015; Cigdem and Ozturk 2016; Pappas et al. 2017), it was shown that perceived ease of use exerts a direct and positive effect on perceived usefulness ($\beta = 0.66$; *p* value < 0.01). This indicates that, the easier to use the MOOC is considered to be, the more useful (beneficial and functional) it will be perceived as. However, the relationship between ease of use and MOOC use intention (H2) could not be confirmed ($\beta = 0.06$; *p* value: not significant). This result contrasts with those of other earlier studies (Roca and Gagné 2008; Huanhuan and Xu 2015; Pappas et al. 2017); but it is in line with the findings of Mohammadi (2015), Xu (2015) and Cigdem and Ozturk (2016), who also found this relationship to have no significance. According to Mohammadi (2015), in the education context, some studies are consistent with the premise that the acceptance of e-learning is directly influenced by perceived usefulness, but indirectly, through perceived ease of use. Therefore, the specific sphere of investigation (use intention for one technological system in particular), together with other factors inherent in the sample population (such as cultural characteristics or age and gender) may explain the differences between the findings of different studies for the relationship between perceived ease of use and use intention.

H3, which proposed the effect of vividness of course content on MOOC use intention, found no empirical support in the present investigation ($\beta = 0.07$; *p* value: not significant). This result is in contrast with the recent study undertaken by Huang et al. (2017). Given that this aspect has very low repercussions in research dealing with distance education, it is important to note that these authors focus on revisit intention, which suggests there may be a moderating effect of the "previous experience" variable. That is to say, for users who have never participated in a MOOC before, it may be considerably more difficult to perceive the vividness of the course content; and therefore, it would not be a significant variable in use intention.

The relationship between perceived interactivity and use intention in H4 was rejected, in view of the results obtained ($\beta = -0.10$; *p* value: not significant). While there is very limited literature on the interactivity of e-learning courses as a significant factor in their use intention, nevertheless this result contrasts with those of other studies (e.g. Huanhuan and Xu 2015; Hone and El Said 2016; Huang et al. 2017). It is worth mentioning some of the issues that may explain this difference. Although the present research coincides with some of the references mentioned in the analysis of interactivity between teacher and students, as we have seen, Huang et al. (2017) demonstrated its effect on revisit intention for a MOOC, whereas Hone and El Said (2016) demonstrated the effect of the same type of interactivity on MOOC student retention. Elsewhere, Lin and Huang (2008) found empirical support for interactivity (understood as interdependence of tasks) and the use of knowledge-management systems in professional working environments. Taking all this into account, it can be affirmed that there are peculiarities in the hypothesis that may have affected the differentiating result obtained in the present research—such as user previous experience or certain motivations related to users' work environment.

H5 and H6, which related to motivations and use intention, could not be entirely rejected. On the one hand, the direct and positive effect of controlled motivation on use intention (H5) could not be confirmed ($\beta = -0.02$; p value: not significant). This result echoes those obtained by Zhou (2016), albeit that study established indirect relationships between controlled motivation and intention, via behavioral control, attitude and subjective norms. Nor could Mikalef et al. (2016) corroborate the positive effect of social influence (considered to be similar to controlled motivation) on the behavioral intention of users to adopt video-based learning models. However, the results of the present investigation contrast with the findings of Lee (2010) and Xu (2015), which verified the direct and positive relationship between subjective norms (understood as perceived social pressure or influence) and the intention to use e-learning and MOOCs, respectively. The results also contrast with the findings of Xiong et al. (2015), regarding social motivation as a variable that influences MOOC user retention, but indirectly, via intrinsic and extrinsic motivation. The heterogeneity of the study participants and their lack of experience of MOOCs (as well as the fact that many of them had never even heard of such courses) may explain the result obtained. Although social pressure or influence may impact on the behavior of individuals, it should perhaps also be considered a multi-stage process, including an initial information-search stage (following a personal recommendation) prior to the decision to participate in a course of these characteristics.

On the other hand, H6, which proposed the direct and positive effect of autonomous motivation on MOOC user intention, found empirical support in the present study ($\beta = 0.48$; p value < 0.01). This result coincided with the findings of Xiong et al. (2015), although those authors established an indirect relationship between both intrinsic and extrinsic motivation and MOOC user retention, via user commitment to the course. Also of note is the similarity between the result of the present study and that of Zhou (2016), which approaches autonomous motivation in the same way as the present study, in both its intrinsic and extrinsic dimensions. In the work of Zhou (2016), however, the empirical support is also based on the indirect effect on use intention, via behavioral control and attitude. Therefore, it can be affirmed that autonomous or individual motivation is a significant predictor of MOOC use intention.

H7 and H8, both relating to entertainment, could not be entirely rejected. In contrast to other studies examined in the literature review (Roca and Gagné 2008; Lee et al. 2009; Wojciechowski and Cellary 2013; Alraimi et al. 2015), the direct and positive effect of entertainment perceived by the user on their intention to participate in a MOOC could not be verified ($\beta = -0.10$; p value: not significant). However, this result does coincide with that of Lee (2010), which, while demonstrating the indirect effect of entertainment on continued use intention for e-learning (via attitude), could not verify its direct influence. This difference between the present results and those of the extant literature may be attributable to, on the one hand, the difficulty the user faces in capturing the entertainment offered by the course prior to starting it; and, on the other hand, to the different technological contexts and other characteristics of the particular participants in the study (systems that may be associated with being more entertaining to use, and users who are more accustomed to—or more predisposed to—using new technologies). Specifically, in the case of H8, this was validated ($\beta = 0.22$; p value < 0.05), corroborating the direct and positive influence of perceived entertainment on MOOC user satisfaction. This finding coincides with those from the literature analyzed for the present study (Thong et al. 2006; Qin and Xu 2007; Alraimi et al. 2015). It can therefore be affirmed that the expectation of a pleasant experience is a predictor of perceived satisfaction in the context of MOOCs.

With regard to the relationship between perceived course quality and satisfaction, H9 found empirical support ($\beta = 0.51$; p value < 0.01). This result is in line with those of Udo et al. (2011), Ayala et al. (2014) and Zambrano (2016). Therefore, it is affirmed that course quality is a key aspect for users, as it influences their satisfaction—which, in turn, influences their intention to participate in MOOCs (as will be discussed later in this paper). Furthermore, considering that the sample population under analysis included both those who had some experience of this type of course, and those with none, this finding corroborates the importance of perceived quality as a factor that students may take into account even prior to participating in a MOOC, this variable having been found to exert the greatest effect on satisfaction.

H10, H11 and H12, which dealt with perceived usefulness, could not be entirely rejected. With regard to H10, it was demonstrated that usefulness exerts a direct and positive effect on user satisfaction ($\beta = 0.38$; p value < 0.01). This result adds to the findings obtained in several other studies (Del Barrio et al. 2015; Cigdem and Ozturk 2016; Zambrano 2016). It is shown, then, that user perception of the efficiency of learning via MOOCs is reflected in the level of user satisfaction. However, H11 had to be rejected, as the influence of usefulness on use intention could not be verified ($\beta = 0.01$; p value: not significant). In marked contrast to the extensive justification of this relationship presented in the literature (Del Barrio et al. 2015; Huanhuan and Xu 2015; Mohammadi 2015; Xu 2015; Cigdem and Ozturk 2016; Pappas et al. 2017), the present result coincides only with the findings of Wojciechowski and Cellary (2013). It should be noted, however, that the latter work analyzes use intention in augmented reality learning environments among secondary school students, which involves certain differences compared to the present outcome. The explanation for this result may lie in the heterogeneous characteristics of the sample profile under study (comprising different age groups, educational levels, and extent of Internet and social network experience, for instance). Although usefulness exerted no direct influence on MOOC use intention among the sample under analysis, this factor should be considered in the indirect relationship via satisfaction and emotions (as explained later in this paper).

Regarding H12 and the proposed relationship between usefulness and emotions, in line with the research conducted by Pappas et al. (2017) it was shown that perceived usefulness has a major direct and positive effect on the emotions of MOOC users ($\beta = 0.79$; p value < 0.01). This finding may indicate that users are capable of anticipating and valuing the positive consequences derived from participating in these courses, associating them with a sense of enjoyment and emotion.

H13, which dealt with the relationship between emotions and use intention, achieved a confidence level of 90% and therefore could not be rejected ($\beta = -0.15$; p value < 0.10). However, given the lack of similar studies, there was little empirical support for this hypothesis. Although the result is comparable with that obtained by Pappas et al. (2017), who also confirmed the direct effect of students' emotions on their intention to adopt a video-task-based learning system, the two differ in the level of significance and the direction of the relationship. These differences may be due to the sample studied in the present work, which is bigger and more heterogeneous than that of Pappas et al. (2017). At the same time, as the literature indicates, assessing emotions is a challenging task—and all the more so, given the high percentage of respondents who had no previous experience of this learning methodology and, in many cases, had never even heard of it. Given the definition of emotion as the user's mental state of preparedness that arises from their cognitive evaluation of events or thoughts (Hibbeln et al. 2016), it seems logical to assume that the respondents displayed major differences when evaluating the MOOC, which would have repercussions for the results obtained. Further studies are required in the future to shed light on this issue.

Finally, H14 also found empirical support ($\beta = 0.54$; p value < 0.01). This result suggests that satisfaction is the most important predictor of use intention, a conclusion that has been drawn by many previous studies (Udo et al. 2011; Ayala et al. 2014; Alraimi et al. 2015; Del Barrio et al. 2015; Mohammadi 2015; Shahijan et al. 2016). It can therefore be affirmed that, the greater the satisfaction among users, the greater their MOOC use intention. It is also important to highlight the fact that, although the direct effects of usefulness and entertainment on use intention could not be proven, there was a clear indirect effect, mediated via satisfaction. Furthermore, given the assumption that use precedes satisfaction (Mohammadi 2015), this result is of particular interest, as it takes into account the responses of both those participants with some experience of MOOCs and those who have never experienced them.

Figure 2 shows the values of the standardized coefficients between constructs, together with the coefficients of determination for the dependent variables.

Conclusions, limitations and future lines of research

Theoretical conclusions

The growing popularity of MOOCs is leading some observers to consider them a disruptive technology—albeit this mode of learning facilitates the democratization of access to higher education—reflecting the principles of the Web 2.0 phenomenon. However, given the short trajectory of MOOCs to date, evidence-based knowledge of their operation is reflected in a very limited range of literature, in which researchers examine extremely diverse aspects in an endeavor to understand the mechanisms that help generate and develop such learning activities and their social, cultural, economic and business effects.

One of the more under-studied topics to date is that of student motivation to participate in MOOCs, particularly in the case of users who are unsure or undecided about signing up. The present work focuses on this particular area, with the aim of shedding light on the complex framework of relationships that influence user perceptions and decisions. To this end, a structural equation model

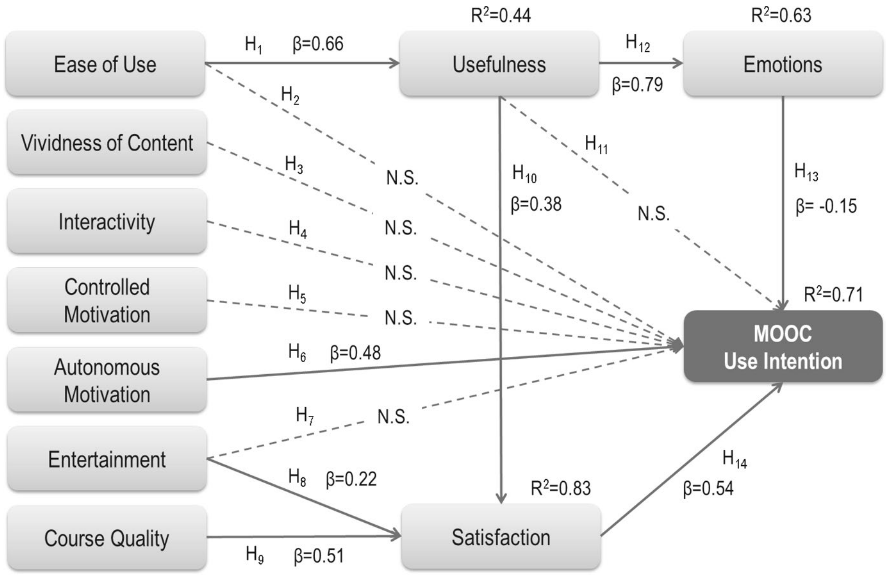

Fig. 2 Results of the proposed SEM

was developed, which considered a series of variables defined on the basis of the prior literature review. The subsequent statistical analyses were based on the data collected by means of an online survey that sought the opinions of a sample population of diverse characteristics on their MOOC use intention. Following an evaluation of the structural model and verification of the adequacy of the fit of the measurement model, the research hypotheses were tested.

With regard to the proposed objective, results obtained from the use of the technology acceptance model, self determination theory and SERVQUAL confirm the significant direct or indirect impact of some of the variables incorporated into the research model (entertainment and satisfaction) on MOOCs. Therefore, the study concludes that the research objectives have been met.

In particular, the results showed that half of the relationships between the latent constructs found empirical support in the literature. It was observed that perceived ease of use is a major factor that exerts a direct and positive influence on perceived usefulness, indicating that, the more a MOOC is perceived to be easy to use, the more useful (beneficial and functional) the user will consider it to be. With regard to the relationship between usefulness and emotions—in line with the study previously undertaken by Pappas et al. (2017), who proposed and demonstrated this association—the present work verified the particularly strong role played by usefulness as a predictor of user emotions. This result offers additional empirical support to the work of these authors, who based their study on users who already used video-based tasks in their learning process. This suggests that users are capable of valuing the positive consequences of using MOOCs, deriving a sense of enjoyment and emotion, even before using the system for real.

Just as the literature has demonstrated in many studies, the relationship between satisfaction and use intention was also verified. Perceived satisfaction was not only found to be the most critical predictor; in addition, it was shown to be a mediating variable between other factors (such as usefulness, entertainment and course quality) and MOOC use intention. Given the broad assumption that use precedes satisfaction, this result is of particular interest: satisfaction can be perceived and can therefore act as a significant driver of future use (Mohammadi 2015). This, despite the fact that the individuals in the sample population had varying degrees of knowledge and prior experience in e-learning and MOOCs.

Another noteworthy variable that explains use intention is autonomous motivation, understood as the set of internal incentives that drive human behavior. Given the scarcity of previous works with which to compare this result (and the fact that the few works that do exist establish indirect relationships between this type of motivation, or similar, and use intention), this finding is of particular importance. It demonstrates the direct and positive effect of individual motivation on MOOC use intention, via the responses of those users who lack previous experience with this form of learning. Meanwhile, in line with numerous other studies, the results of the present research verified the direct and positive effect of entertainment, usefulness and course quality on user satisfaction. Of these, course quality is the variable with the greatest effect on satisfaction. It can thus be affirmed that user expectations regarding a pleasant experience, the effectiveness of the learning process and the quality of the course are, taken together, predictors of satisfaction in the context of MOOCs.

Turning again to those relationships proposed in the model that did not find empirical support, one particular case—that of the influence of emotions on MOOC use intention—is of special interest. Although this relationship achieved significance (with a 90% confidence interval), this was in the opposite direction to that obtained by Pappas et al. (2017). Bearing in mind the lack of additional works with which to contrast this result, the differences between the two studies may be explained by the different sample profiles and by the inherent difficulty of measuring emotions.

Some of the relationships proposed in the model that established the direct effect of a range of variables on MOOC use intention were not significant. For example, the influence of ease of use on use intention could not be proven—a result in line with those of Mohammadi (2015), Xu (2015) and Cigdem and Ozturk (2016). This was also in line with the assumption that ease of use does not always constitute a strong factor or that it may influence indirectly via other variables, specifically in the context of e-learning adoption. Similarly, neither vividness of content nor interactivity demonstrated a significant effect on use intention—a result that is in contrast to the recent conclusions of Huang et al. (2017), among others. It may be that the very limited coverage of these associations in the literature, the particular sphere of application of the present study and other issues associated with the sample under analysis are all aspects that could explain the divergence between the findings of different studies.

Controlled motivation, entertainment and usefulness were also found not to be factors predictive of MOOC use intention. Unlike in various other studies that were reviewed, each of these non-significant relationships shared a certain similarity with other previous works. For example, like Mikalef et al. (2016), the present study found no positive effect between controlled motivation (labeled "social influence" by those authors) and user behavioral intention. Nor could Zhou (2016), who established several indirect relationships between these variables, verify such an impact. Elsewhere, the findings of Lee (2010) regarding the non-significant relationship between perceived entertainment and use intention also coincided with those of the present study. Also noteworthy is the similarity with the results of Wojciechowski and Cellary (2013) regarding the lack of significance of usefulness on use intention.

Bearing in mind the heterogeneity of the students (due to the open nature of these courses) and the growth in participant numbers (including first-time subscribers), the present results can be useful to those managing online Higher Education.

Future lines of research

The academic and professional interest in this form of learning calls for theoretical instruments to be developed and applied, to contribute to exploring the factors that motivate students to participate in MOOCs. In the present research, not all of the constructs in the model were represented equally and use intention may have been influenced by other factors that were not considered in the study, such as the previous knowledge required to undertake a given course. Future studies should therefore include more variables and identify other relationships between them, or even assess the indirect effect of the variables used in the present model.

Interactivity, for example, is only addressed here in the context of the teacher and the student, not between the students themselves. Similarly, given that the literature has demonstrated that positive emotions are more important than negative ones, the present investigation only examined the former. However, as peer-working among students is a major feature of MOOCs and given that learners may experience both negative and positive emotions simultaneously, future studies on the topic could consider broadening both of these constructs. Elsewhere, to analyze various dimensions of quality, future works could include different, more specific, statements, bearing mind the extremely broad variety of MOOCs, of institutions offering such programs, and of participant characteristics. In the same way, it would be useful to determine other aspects of individual motivation, including extrinsic motivators such as the acquisition of a given skill or academic certification from a highly prestigious institution.

With regard to some of the demographic data collected in the present study, one potential area of interest for the future is to analyze the possible moderating effect of other variables linked to the profile of the user (age, gender, educational background, level of knowledge in Internet use and social networking, and so on). The role of previous experience as a determining factor in MOOC use (adoption and continued use) would be of particular interest. In contrast to the present approach, which examines one single but heterogeneous group, a future study could test the factors with the greatest relevance for each group, according to its characteristics. In this way, it could contribute to improving the results of the learning process by developing different strategies based on different student profiles.

In this sense, despite the universal nature of MOOCs, they present uneven development and impact across different geographical areas. Future studies should therefore examine the access requirements of MOOCs (the necessary infrastructure and skills), language, and other cultural aspects. The information that this type of studies could provide (including comparative studies between groups of different cultures or nationalities) would facilitate the creation of courses that are a well-matched with students from given social contexts.

Future research is also proposed into the popularity of educational platforms (learning management systems, or LMS) as business models, as a means of improving their positioning in the online higher education environment. This type of study, which could include factors such as brand image, satisfaction, user recommendation (e-WOM), and loyalty, would generate invaluable information for higher education institutions and their providers specializing in MOOC tools and technology.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Appendix: Scales and items used in the study

Construct	Questionnaire items adapted to the present study	References
Perceived ease of use (PEU)	1. I find it easy to be good at using MOOCs 2. I find it easy to learn how to work with MOOC systems 3. I find it easy to get the MOOC system to do what 4. I want it to 5. I find it easy to use MOOCs	Sun et al. (2008)
Perceived usefulness (PU)	1. Using MOOCs would improve my learning performance 2. Using MOOCs would increase my learning efficiency 3. Using MOOCs would be useful for me	Alraimi et al. (2015)
Emotions (EM)	1. Using MOOCs would be pleasant 2. Using MOOCs would be exciting 3. Using MOOCs would make me feel good	Pappas et al. (2017)
Vividness of content (VC)	1. The educational process of MOOCs seems lively 2. The educational process of MOOCs seems energetic 3. The educational process of MOOCs seems to be enlivening for the senses 4. I could take in the learning process of MOOCs via different sensory channels	Huang et al. (2017)

Construct	Questionnaire items adapted to the present study	References
Perceived interactivity (PI)	1. The interactivity between teacher and student on a MOOC would enable me to better understand the content 2. The interactivity between teacher and student on a MOOC would enable me to learn more from the course 3. The interactivity between teacher and student on a MOOC would enable me to use summaries and compare them with others 4. The interactivity between teacher and student on a MOOC would enable me to resolve my questions	Huang et al. (2017)
Controlled motivation (CM)	1. I would use a MOOC if other people told me I should do so 2. I would feel under pressure from my friends/family/partner to use MOOCs 3. I would use a MOOC if my friends/family/partner were to tell me I should do so 4. I would feel embarrassed if I were not to use MOOCs in order to learn	Zhou (2016)
Autonomous motivation (AM)	1. I think using MOOCs is important for learning 2. I value the benefits of using MOOCs 3. I think it's important to make an effort to use MOOCs to learn 4. I would study via MOOCs because it is important to do so 5. I would enjoy myself studying via MOOCs	Zhou (2016)
Perceived entertainment (PE)	1. Using MOOCs seems pleasant 2. I would enjoy myself using MOOCs 3. I would find it fun to use MOOCs	Alraimi et al. (2015)
Perceived course quality (PCQ)	4. The fact that MOOCs are conducted via the Internet means they are of better quality than other (offline) courses 5. The quality of MOOCs may compare favorably with that of other courses I have undertaken 6. I do not think the quality of a MOOC is influenced by the fact that it is undertaken via the Internet	Sun et al. (2008)
Perceived satisfaction (PS)	1. I would be satisfied with my decision to undertake a MOOC 2. If I had the chance to undertake a MOOC, I would be delighted to do so 3. I would be very satisfied with a MOOC 4. I feel that MOOCs are well-suited to my needs 5. I will undertake as many MOOCs as I can 6. I find the way MOOCs work disappointing 7. Undertaking a MOOC would be more difficult than other courses I have taken	Sun et al. (2008)

Construct	Questionnaire items adapted to the present study	References
Use intention (UI)	1. I intend to use MOOCs in the future 2. My overall intention to use MOOCs in the future is very high 3. I would use MOOCs regularly in the future 4. I would think about using MOOCs	Pappas et al. (2017)

References

Adamopoulos, P. (2013). What makes a great MOOC? An interdisciplinary analysis of student retention in online courses. In *34th International conference on information systems: ICIS 2013* Association for Information Systems.

Aguaded, I., & Medina-Salguero, R. (2015). Criterios de calidad para la valoración y gestión de MOOC. *RIED: Revista Iberoamericana de Educación a Distancia, 18*(2), 119–143. https://doi.org/10.5944/ried.18.2.13579.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

Alexandron, G., Yoo, L. Y., Ruipérez-Valiente, J. A., Lee, S., & Pritchard, D. E. (2019). Are MOOC learning analytics results trustworthy? With fake learners, they might not be! *International Journal of Artificial Intelligence in Education, 29,* 484–506.

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers and Education, 80,* 28–38. https://doi.org/10.1016/j.compedu.2014.08.006.

Ayala, C., Dick, G., & Treadway, J. (2014). The MOOCs are coming! Revolution or fad in the Business School? *Communications of the Association for Information Systems*: Vol. 35, Article 12. Available at http://aisel.aisnet.org/cais/vol35/iss1/12.

Beaudry, A., & Pinsonneault, A. (2010). The other side of acceptance: Studying the direct and indirect effects of emotions on information technology use. *MIS Quarterly, 34*(4), 689–710. https://doi.org/10.2307/25750701.

Brahimi, T., & Sarirete, A. (2015). Learning outside the classroom through MOOCs. *Computers in Human Behavior, 51,* 604–609. https://doi.org/10.1016/j.chb.2015.03.013.

Camilleri, A. F., Ehlers, U. D., Palowski, J. (2014). State of the art review of quality issues related to open educational resources (OER). *JRC IPTS report*. Luxembourg: Publication Offices of the European Union. http://doi.org/10.2791/80171.

Castañeda, J. A., Muñoz-Leiva, F., & Luque, T. (2007). Web acceptance model (WAM): Moderating effects of user experience. *Information and Management, 44*(4), 384–396. https://doi.org/10.1016/j.im.2007.02.003.

Castaño, C., Maiz, I., & Garay, U. (2015). Percepción de los participantes sobre el aprendizaje en un MOOC. *RIED. Revista Iberoamericana De Educación a Distancia, 18*(2), 197–221. https://doi.org/10.5944/ried.18.2.13444.

Chang, J. J., Lin, W. S., & Chen, H. R. (2019). How attention level and cognitive style affect learning in a MOOC environment? Based on the perspective of brainwave analysis. *Computers in Human Behavior, 100,* 209–217.

Cigdem, H., & Ozturk, M. (2016). Factors affecting students' behavioral intention to use LMS at a Turkish post-secondary vocational school. *International Review of Research in Open and Distance Learning*. https://doi.org/10.19173/irrodl.v17i3.2253.

Conole, G. (2016). MOOCs as disruptive technologies: strategies for enhancing the learner experience and quality of MOOCs. *RED. Revista de Educación a Distancia*. https://doi.org/10.6018/red/50/2.

Daniel, J., Vázquez, E., & y Gisbert, M. (2015). El futuro de los MOOC: ¿aprendizaje adaptativo o modelo de negocio? *RUSC. Universities and Knowledge Society Journal, 12*(1), 64–74. https://doi.org/10.7238/rusc.v12i1.2475.

Del Barrio, S., Arquero, J. L., & Romero-Frías, E. (2015). Personal learning environments acceptance model: The role of need for cognition, e-learning satisfaction and students' perceptions. *Journal of Educational Technology and Society, 18*(3), 129–141.

Del Barrio, S. & Luque, T (2012). Análisis de Ecuaciones Estructurales, en Luque, T. (coord.), Técnicas de análisis de datos en investigación de mercados. Madrid, España: Ediciones Pirámide.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*. https://doi.org/10.2307/3151312.

Fortin, D. R., & Dholakia, R. R. (2005). Interactivity and vividness effects on social presence and involvement with a web-based advertisement. *Journal of Business Research, 58,* 387–396. https://doi.org/10.1016/S0148-2963(03)00106-1.

García-Martínez, C., Cerezo, R., Bermúdez, M., & Romero, C. (2019). Improving essay peer grading accuracy in massive open online courses using personalized weights from student's engagement and performance. *Journal of Computer Assisted Learning*. https://doi.org/10.1111/jcal.12316.

Gupta, K. P. (2019). Investigating the adoption of MOOCs in a developing country. *Interactive Technology and Smart Education*. https://doi.org/10.1108/itse-06-2019-0033.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis*. London: Pearson.

Hibbeln, M. T., Jenkins, J. L., Schneider, C., Valacich, J., & Weinmann, M. (2016). Inferring negative emotion from mouse cursor movements. *MIS Quarterly, 41*(1), 1–21.

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers and Education, 98,* 157–168. https://doi.org/10.1016/j.compedu.2016.03.016.

Hood, N., & Littlejohn, A. (2016). MOOC Quality: The need for new measures. *Journal of Learning for Development-JL 4D*, *3*(3). Retrieved from http://www.jl4d.org/index.php/ejl4d/article/view/165.

Hu, X., Wu, G., Wu, Y., & Zhang, H. (2010). The effects of Web assurance seals on consumers' initial trust in an online vendor: A functional perspective. *Decision Support Systems, 48*(2), 407–418.

Huang, L., Zhang, J., & Liu, Y. (2017). Antecedents of student MOOC revisit intention: Moderation effect of course difficulty. *International Journal of Information Management, 37*(2), 84–91. https://doi.org/10.1016/j.ijinfomgt.2016.12.002.

Huanhuan, W., & Xu, L. (2015). Research on technology adoption and promotion strategy of MOOC. *The Institute of Electrical and Electronics Engineers, Inc.* (IEEE) Conference proceedings (pp. 907–910). http://doi.org/10.1109/ICSESS.2015.7339201.

Hyo-Jeong So, Y. J. J., & Kim, H. E. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computer and Education*. https://doi.org/10.1016/j.compedu.2018.01.003.

Inamorato dos Santos, A., Punie, y., Castaño-Muñoz, J. (2016). Opening up education: A support framework for higher education institutions. *JRC Science for Policy Report*, EUR 27938 EN. https://doi.org/10.2791/293408.

Kay, R. H., & Loverock, S. (2008). Assessing emotions related to learning new software: The computer emotion scale. *Computers in Human Behavior, 24*(4), 1605–1623. https://doi.org/10.1016/j.chb.2007.06.002.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In *Proceedings of the third international conference on learning analytics and knowledge* (pp. 170–179). New York, NY: ACM. https://doi.org/10.1145/2460296.2460330.

Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers and Education, 54*(2), 506–516. https://doi.org/10.1016/j.compedu.2009.09.002.

Lee, B. C., Yoon, J. O., & Lee, I. (2009). Learners' acceptance of e-learning in South Korea: Theories and results. *Computers and Education, 53*(4), 1320–1329. https://doi.org/10.1016/j.compedu.2009.06.014.

Li, K. (2019). MOOC learners' demographics, self-regulated learning strategy, perceived learning and satisfaction: A structural equation modeling approach. *Computers and Education, 132,* 16–30.

Liébana-Cabanillas, F., Muñoz-Leiva, F., & Sánchez-Fernández, J. (2018). A global approach to the analysis of user behavior in mobile payment systems in the new electronic environment. *Service Business, 12*(1), 25–64.

Lin, T. C., & Huang, C. C. (2008). Understanding knowledge management system usage antecedents: An integration of social cognitive theory and task technology fit. *Information and Management, 45*(6), 410–417. https://doi.org/10.1016/j.im.2008.06.004.

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008–2012. *International Review of Research in Open and Distributed Learning, 14*(3), 202–227. https://doi.org/10.19173/irrodl.v14i3.1455.

Ma, L., & Lee, C. S. (2019). Investigating the adoption of MOOC s: A technology user-environment perspective. *Journal of Computer Assisted learning, 35*(1), 89–98.

Magen-Nagar, N., & Cohen, L. (2017). Learning strategies as a mediator for motivation and a sense of achievement among students who study in MOOCs. *Education and Information Technologies, 22*(3), 1271–1290. https://doi.org/10.1007/s10639-016-9492-y.

Mikalef, P., Pappas, I. O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. *The International Journal of Information and Learning Technology, 33*(4), 219–235. https://doi.org/10.1108/ijilt-01-2016-0007.

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior, 45,* 359–374. https://doi.org/10.1016/j.chb.2014.07.044.

Mohapatra, S., & Mohanty, R. (2016). Adopting MOOCs for afforable quality education. *Education and Information Technologies*. https://doi.org/10.1007/s10639-016-9526-5.

Mora, C. E. (2011). La calidad del servicio Y la satisfacción del consumidor. *REMark, 10*(2), 146. https://doi.org/10.5585/remark.v10i2.2212.

Pappas, I. O., Giannakos, M. N., & Mikalef, P. (2017). Investigating students' use and adoption of with-video assignments: Lessons learnt for video-based open educational resources. *Journal of Computing in Higher Education, 29*(1), 160–177. https://doi.org/10.1007/s12528-017-9132-6.

Pérez-Sanagustín, M., Hilliger, I., Alario-Hoyos, C., Kloos, C. D., & Rayyan, S. (2017). H-MOOC framework: Reusing MOOCs for hybrid education. *Journal of Computing in Higher Education, 29*(1), 47–64.

Pursel, B. K., Zhang, L., Jablokow, K. W., Choi, G. W., & Velegol, D. (2016). Understanding MOOC students: Motivations and behaviours indicative of MOOC completion. *Journal of Computer Assisted Learning, 32*(3), 202–217.

Puska, A., Ejubovic, A., & Beganovic, A. I. (2016). Student feedback as a guideline for higher education quality enhancement. *Ekonomika, 62*(4), 39–53. https://doi.org/10.5937/ekonomika1604039P.

Qin, M., & Xu, S. (2007). An extended expectation confirmation model for information systems continuance. In *2007 International conference on wireless communications, networking and mobile computing* (pp. 3874–3877). IEEE. https://doi.org/10.1109/wicom.2007.959.

Rabin, E., Kalman, Y. M., & Kalz, M. (2019). An empirical investigation of the antecedents of learner-centered outcome measures in MOOCs. *International Journal of Educational Technology in Higher Education, 16*(1), 14.

Ray, S., Ow, T., & Kim, S. S. (2011). Security assurance: How online service providers can influence security control perceptions and gain trust. *Decision Sciences, 42*(2), 391–412.

Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science, 363*(6423), 130–131.

Riehemann, J., Hellmann, J. H., & Jucks, R. (2018) "Your words matter!" Relevance of individual participation in xMOOCs. *Active Learning in Higher Education.* https://doi.org/10.1177/1469787418779154.

Rienties, B., & Rivers, B. A. (2014). Measuring and understanding learner emotions: Evidence and prospects. *Learning Analytics Review, 1,* 1–28.

Roca, J. C., & Gagné, M. (2008). Understanding e-learning continuance intention in the workplace: A self-determination theory perspective. *Computers in Human Behavior, 24*(4), 1585–1604. https://doi.org/10.1016/j.chb.2007.06.001.

Román, A. P., González, A. B., & Idoeta, C. M. (2014). Análisis del proceso de generación de lealtad en el entorno on-line a través de la calidad del servicio y de la calidad de la relación. *Revista Europea de Dirección y Economía de la Empresa, 23*(4), 175–183. https://doi.org/10.1016/j.redee.2014.09.003.

Ruiz, M., Palací, F. J., Salcedo, A., & Garcés, J. (2010). E-satisfacción: Una aproximación cualitativa. *Acción psicológica*. http://doi.org/10.5944/ap.7.1.209.

Shahijan, M. K., Rezaei, S., & Amin, M. (2016). International students' course satisfaction and continuance behavioral intention in higher education setting: An empirical assessment in Malaysia. *Asia Pacific Education Review, 17*(1), 41–62. https://doi.org/10.1007/s12564-015-9410-9.

Shanghai Ranking (2017). Global Ranking of Academic Subjects. Retrieved from https://drive.google.com/file/d/0Bw2rAawlHlvBYndVM2x5cHREdWs/view.

Sivo, S. A., Fan, X., Witta, E. L., & Willse, J. T. (2006). The search for "optimal" cutoff properties: Fit index criteria in structural equation modeling. *The Journal of Experimental Education, 74*(3), 267–288.

Song, Z. X., Cheung, M. F., & Prud'Homme, S. (2017). Theoretical frameworks and research methods in the study of MOOC/e-learning behaviors: A theoretical and empirical review. In *New ecology for education—Communication X learning* (pp. 47–65). Springer, Singapore. https://doi.org/10.1007/978-981-10-4346-8_5.

Sun, P. C., Tsai, T. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers and Education, 50*(4), 1183–1202. https://doi.org/10.1016/j.compedu.2006.11.007.

Tang, H., Xing, W., & Pei, B. (2018). Exploring the temporal dimension of forum participation in MOOCs. *Distance Education, 39*(3), 353–372.

Teo, T., Sang, G., Mei, B., & Hoi, C. K. W. (2019). Investigating pre-service teachers' acceptance of Web 2.0 technologies in their future teaching: A Chinese perspective. *Interactive Learning Environments, 27*(4), 530–546.

Thong, J. Y. L., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation–confirmation model for information technology continuance. *International Journal of Human-Computer Studies, 64*(9), 799–810. https://doi.org/10.1016/j.ijhcs.2006.05.001.

Udo, G. J., Bagchi, K. K., & Kirs, P. J. (2011). Using SERVQUAL to assess the quality of e-learning experience. *Computers in Human Behavior, 27*(3), 1272–1283. https://doi.org/10.1016/j.chb.2011.01.009.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926.

Wells, W. D. (1997). *Measuring advertising effectiveness*. London: Routledge.

Wojciechowski, R., & Cellary, W. (2013). Evaluation of learners' attitude toward learning in ARIES augmented reality environments. *Computers and Education, 68,* 570–585. https://doi.org/10.1016/j.compedu.2013.02.014.

Xing, W. (2018). Exploring the influences of MOOC design features on student performance and persistence. *Distance Education*. https://doi.org/10.1080/01587919.2018.1553560.

Xiong, Y., Li, H., Kornhaber, M. L., Suen, H. K., Pursel, B., & Goins, D. D. (2015). Examining the relations among student motivation, engagement, and retention in a MOOC: A structural equation modeling approach. *Global Education Review, 2*(3), 23–33.

Xu, F. (2015). Research of the MOOC study behavior influencing factors. In *Proceedings of international conference on advanced information and communication technology for education* (pp. 18–22). Amsterdam: Atlantis Press. https://doi.org/10.2991/icaicte-15.2015.5.

Yuan, L., & Powell, S. (2013). MOOCs and open education: Implications for higher education. *White Paper*. Retrieved from http://publications.cetis.org.uk/wp-content/uploads/2013/03/MOOCs-and-Open-Education.pdf.

Zambrano, J. (2016). Factores predictores de la satisfacción de estudiantes de cursos virtuales. *RIED. Revista Iberoamericana de Educación a Distancia*, *19*(2), 217–235. http://doi.org/10.5944/ried.19.2.15112.

Zhang, J. (2016). Can MOOCs be interesting to students? An experimental investigation from regulatory focus perspective. *Computers and Education, 95,* 340–351. https://doi.org/10.1016/j.compedu.2016.02.003.

Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers and Education, 92,* 194–203. https://doi.org/10.1016/j.compedu.2015.10.012.

Irma Pozón-López has a degree in Communication Sciences, a Master in e-Learning: new technologies for learning through the internet from the University of Seville and a Master in Marketing and consumer behavior from the University of Granada. Her main area of research and interest is the field of education and new technologies. She has published a recent article about customer satisfaction and intention to use Massive Open Online Courses (MOOCs). Besides, she is a communication and education consultant for telecommunication companies.

Elena Higueras-Castillo has a degree in Business and Administration Science and a Master in Marketing and Consumer Behavior from the University of Granada. Her main area of research and interest is the field of consumer ecological behavior and its values, analyzing it through the adoption of new technologies respectful of the environment. She has published recent articles about the adoption of renewable energies on European and Latin American consumers. Also, she specializes in the consumer adoption of electro mobility.

Francisco Muñoz-Leiva is Full Professor in Marketing and Market Research and holds a Ph.D. in Business Sciences from the University of Granada (Spain). His main research interests are the retail marketing, Internet consumer behavior and, recently, neuromarketing. His recent research have been published in more than 50 papers in journals indexed in WoS, such as Physiology & Behavior, Journal of Business Research, International Journal of Advertising, Tourism Management, Soft Computing, Expert Systems with Applications, Online Information Review, Information & Management, Computers in Human Behavior, Quality & Quantity or Journal of Environmental Management, as well as in national and international conferences.

Francisco J. Liébana-Cabanillas holds a Ph.D. in Business Sciences from the University of Granada (Spain). His main area of research and interest in the field is the effectiveness of mobile and online banking, Internet consumer Behavior, e-banking acceptance, social media and tourism. He has published articles on these topics in various academic journals, such as Tourism Management, International Journal of Information Management, Computers in Human Behavior, Expert Systems with Applications, Industrial Management & Data Systems, Technological Forecasting and Social Change among others, as well as in national and international conferences (EMAC, AEMARK, Hispanic-Lusitanian Congress in Scientific Management, AEDEM, GIKA, Global Management, etc.).