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Correlation analysis between expectancy-value and achievement goals in MOOCs on energy sustainability: Profiles with higher engagement

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Correlation analysis between expectancy-value and achievement goals in MOOCs on energy sustainability

Profiles with higher engagement

Abstract

Purpose – This research seeks to analyze the interrelationship that exists between expectancy-value and achievement goals as factors that are decisive for participants' higher engagement in 12 MOOCs on energy sustainability and to determine the profile of participants achieving higher success rates.

Design/methodology/approach – A qualitative–quantitative study of correlational and descriptive scope is carried out on two instruments based on pre- and post-tests of 6,029 participants, which is followed by a Qualitative Data Analysis (QDA) distributed by code families to identify participants' main motivations to take MOOCs.

Findings – The results showed a positive moderate-high correlation between expectancy-value and achievement goals, which means in a practical sense that the participants' subjective estimates of the possibility of reaching their goals prior to the beginning of the course were fulfilled, since the intentionality of the subjects-participants was positive with respect to the contents imparted.

Practical implications – The profiles of participants with a higher tendency to successfully finish the course and with high rates of engagement share the following characteristics: i) having previously and successfully finished more than one MOOC; ii) taking the MOOC for work purposes (promotion, seeking better job opportunities, etc.); and iii) having intrinsic motivation, that is, not depending on external factors such as obligations and certifications.

Originality/value – This research suggests that there are pre-educational factors that define the trend of successful completion of MOOCs, based on expectancy-value (e.g., previous experiences with other MOOCs) and achievement goals (e.g., job improvement), with external motivational issues such as completion certificates being less prevalent in the learning intention.

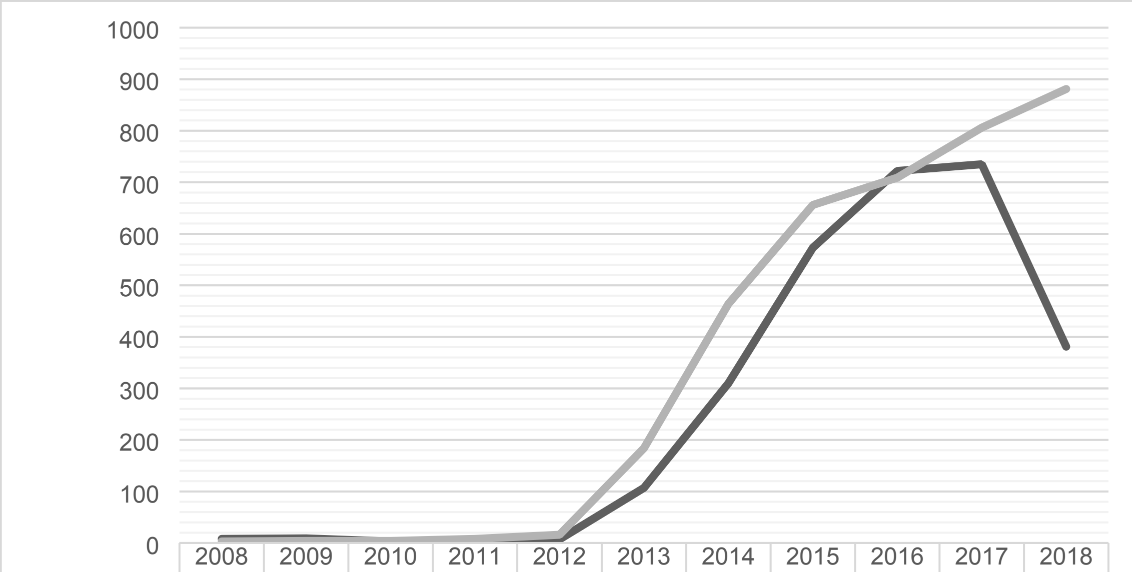
Keywords: E-Learning; Engagement; Motivation.

Paper type Research paper

1. Introduction

Ever since Massive Open Online Courses (MOOCs) were introduced in 2008, they have been very popular in the scientific and academic community because of their great versatility and the fact that they are a flexible educational alternative (Gabel, 2013). Thus, the popularity of MOOCs affects how universities deal with online training and even causes them to be regarded as the next development in e-learning (Castaño *et al*., 2015).

This form of teaching gathers a large number of participants—sometimes hundreds of thousands in only one course—due to its universal accessibility, ubiquity, affordability (free), flexibility, and instructional design. Therefore, the enormous interest of the scientific community in these phenomena is not trivial. In fact, by means of an *ad hoc* analysis of the main international reference databases (Journal Citation Reports and Scopus), a total of 6,596 indexed documents have emerged since 2008 with a clear tendency to grow year-over-year (Figure 1).



	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
JCR	8	9	3	6	7	107	310	573	722	735	381
Scopus	3	4	4	8	16	184	464	656	709	806	881

Figure 1. Publications on MOOCs in indexed JCR/Scopus journals

Note: The Boolean algorithm is used by subject (which includes title, abstract, and keywords) for the exploratory analysis of publications, which is limited to indexed journals from 2008 to 2018. At the time of the exploratory analysis (31/08/2019), not all the documents from 2018 were updated in the database, which could be the reason for the drop in the Journal Citation Reports® 2018.

From this initial exploratory analysis, we can agree with Castaño *et al*. (2015) that a great many emerging lines of research on MOOCs have focussed on the pedagogical and instructional design; interactions among participants; learning perspectives and dimensions, such as motivation and attitudes; and the emerging problem of high dropout rates of students.

On this specific matter, after analyzing 24 MOOCs, Jordan (2013) concludes that the highest completion rate was 19.2%, whereas average graduation rates failed to reach 10% of the starting participants. In another study carried out by the same researcher (Jordan, 2015), a similar completion rate is reasserted (0.7–52.1%, with an average of 12.6%). However, although this aspect remains a topic of academic discussion (for example, Kilgore *et al*., 2015; Kerr *et al*., 2015; Valdivia Vázquez *et al*., 2018; Beltrán Hernández de Galindo, Romero-Rodríguez and Ramírez Montoya, 2019), Liyanagunawardena *et al*. (2014) explain that MOOC students challenge the traditional notion of dropout because with the free and open nature of these courses, dropouts are more related to aspects of dissatisfaction, whether over personal learning goals or failure to fulfil their value expectations. Therefore, the free and asynchronous nature of these courses means that dropouts are not related to external factors (economy or time-related).

Academic literature (*v. gr*. Guajardo Leal, Navarro-Corona and Valenzuela González; Guajardo Leal and Valenzuela González, 2019; Romero-Rodríguez, Ramírez Montoya and Valenzuela González, 2019; 2020) agrees that the high dropout rates of MOOCs are mainly due to erroneous participation patterns and instructional design, since often these courses are nothing more than the digital and audiovisual transformation of a traditional class model (master classes), even though the digital ecosystem requires educational innovation and innovative methods to attract and retain the attention of participants (such as gamification, simulations, project-based learning, flipped classroom, etc.).

Motivations to take a MOOC as opposed to traditional courses are more variable (Kizilcec *et al*., 2013; Milligan *et al*., 2016; Terras and Ramsay, 2016). Traditional courses have a higher component of externally associated motivation (for example to obtain a certificate), whereas MOOC participants' motivations tend to be more intrinsic, such as interest in the topic covered in the course (Bonk *et al*., 2015; de Barba *et al*., 2016; Torres-Toukoumidis *et al*., 2018; Romero-Rodríguez, Ramírez-Montoya and Valenzuela González, 2019), a relationship with their environment of professional development and self-determination and challenge (Barak *et al*., 2016).

Studies such as the one by Zhou (2016) show that the decision to enroll in a MOOC depends largely on how participants see themselves, that is, the methods they employ to assess their preexisting knowledge on the subject, the time available to devote to the course, their resources and digital competencies, and their self-discipline abilities. On the other hand, White *et al*. (2014) explain that the three main reasons for choosing a MOOC are as follows: the fact that they are free, the desire to stay up-to-date with regard to knowledge, and interest in the subject, in that order. Through a series of interviews, Zheng *et al*. (2015) identify four types of motivations to enrol in a MOOC: to satisfy current needs, to prepare for the future (which includes obtaining a certificate), to satisfy a curiosity, and to meet people related to their field of study.

In this sense, Hew and Cheung (2014) mention four other motivational reasons as an incentive to enrol in a MOOC: to enhance or develop knowledge in a specific field, to satisfy curiosity regarding MOOCs, to overcome a personal challenge, and to acquire a qualification. On the other hand, Littlejhon *et al*. (2016) list the importance of the course content in connection with the following aspects of a participant's job: career development, increasing practical abilities, learning enjoyment, and professional growth. In view of the abovementioned reasons, it can be said that there are both extrinsic and intrinsic motivations although only the former are more important in the process of deciding whether to enrol.

2. Intrinsic motivation, expectancy-value and achievement goals

According to the scientific literature, it can be deduced that analyzing graduates from MOOCs has become a common strategy to assess participants' performance (Valdivia Vázquez *et al*., 2018), and with this, fundamentally, motivation has been proven to be a basic predictor to achieve a higher level of engagement (Pursel *et al*., 2016; Xu and Yang, 2016; Shapiro *et al*., 2017).

Motivation is defined by Colman (2016, p. 251) as a 'driving force responsible for the commencement, persistence, direction and vigour of the behaviour addressed toward a goal', while motivation to learn is defined as 'students' desire to learn about the learning materials' (Colquitt *et al*., 2002, p. 679). Naturally, motivation is a hyper-complex and dynamic aspect, in which elements such as interests, achievement goals, system of values and beliefs, self-effectiveness and control coexist (Ryan and Deci, 2000; Torres-Toukoumidis *et al*., 2016). These elements tend to change because of the learning environment, the contents or interactions of the course and more specifically in the MOOCs (de Barba *et al*., 2016).

There are several theoretical perspectives regarding motivation, with the most common one among them being self-determination as propounded by Ryan and Deci (2000), who explain that motivation is higher when it is intrinsic, that is to say, when an attitude or behaviour is present because of free will, pleasure, personal satisfaction, and the need to acquire competencies, all related to the need for self-development.

According to another theory, the one on achievement goals, students pursue goals in two dimensions when learning—control versus performance and focus versus avoidance (Elliot and McGregor, 2001)—which affect how students respond to achievement situations, choose which learning strategies to use and how they face academic challenges.

A third theory, which is the one on expectancy-value, explains that motivation comes from an introspective analysis that students make to understand how learning or an academic task may be useful to them (Eccles and Wigfield, 2002). This way, students should have a proactive and positive attitude toward content that according to this analysis they find interesting—such as future prospects—while this motivation should not be present for content that is unappealing to them. With regard to this, it is important to mention that some researchers (for example, Eccles and Wigfield, 2002; Wigfield and Eccles, 2000) understand that values (such as reasons to enrol in a MOOC) and beliefs of skills (prospective for future success) directly affect performance and persistence in any activity (Figure 2).

It is necessary to point out that the three theories mentioned are not exclusive to each other, having been extensively used as a basis for research on MOOCs (Plante *et al*., 2013), considering that involvement in this type of educational model is voluntary—hence the greater dependence on intrinsic motivation—and that completion essentially depends on participants keeping a good level of engagement during the course (Wigfield and Eccles, 2000).

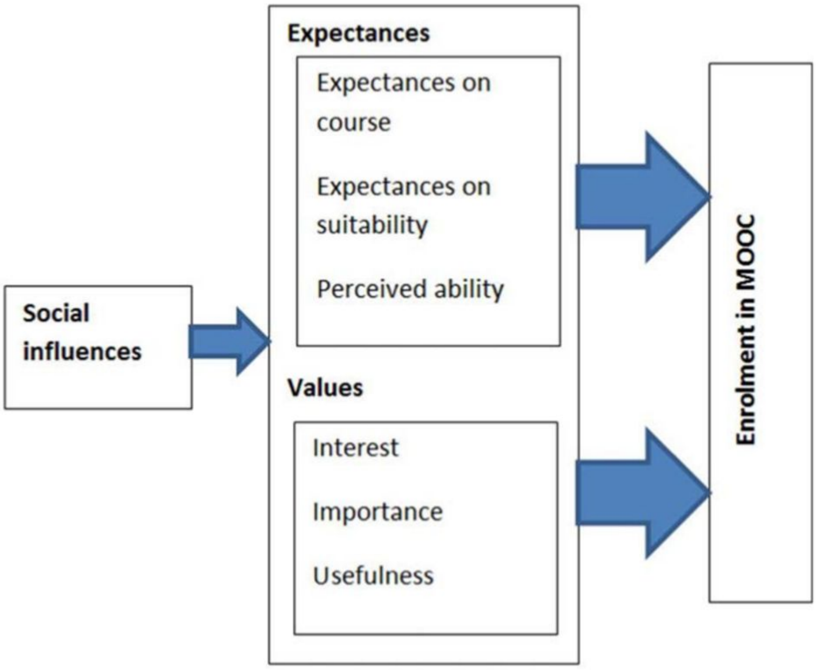


Figure 2. Expectancy-value factors and achievement goals that affect enrollment in a MOOC. Source: Luik *et al*. (2017, p. 158)

As shown in Figure 2, MOOC participants are socially influenced, that is to say, a set of stimuli govern their behaviour and motivations, for example, the emerging need to learn a specific skill (e.g., how to design a website). In this case, participants begin to search for learning environments according to their abilities and interests—time, budget, and preferences. The decision to enrol in a MOOC is made according to expectancy-value and achievement goals, by means of expectations (on the course and its learning materials, on the skills to be acquired and on the comparison between prior knowledge and level of knowledge to be acquired in the MOOC); values, that is, interest in the subject; the importance of the subject for personal and professional development and present and future usefulness of this knowledge (García Espinosa *et al*., 2015; Osuna-Acedo *et al*., 2018).

To this end, participants should establish, prior to taking a MOOC, their motivations and expectancy-value for taking the course, to correctly correlate dropout or fulfilment of achievement goals once the course is completed (Esposito, 2012). Only by gathering this information will it be possible to understand which expectancy-value profile (both on expectations and values) tend to have higher engagement with this teaching/learning method.

According to the foregoing discussion, this paper aims to determine the interrelationship between expectancy-value and achievement goals in MOOCs by means of an exploratory factorial and correlational analysis in courses on energy sustainability in order to verify that (*h0*) there is a direct correlation between both phenomena. The paper also aims to identify the most concurrent expected motivations and usefulness of the courses (expectancy-value) for participants who successfully complete MOOCs in comparison with the achievement goals obtained after completion.

This paper intends to verify that participants with a high rate of expectancy-value—those who have clarity regarding how a specific MOOC could be useful for them—tend to persist (fundamental in engagement)—in order to fulfil achievement goals, that is, to meet their post-course expectations. In addition, the type of expectancy-value (career development, job or business opportunities, academic training, and extended professional relationships, among others) that is most frequent in those completing the course should be determined.

3. Materials and methods

This paper uses a mixed design, with quantitative and qualitative variables for a correlational and descriptive analysis. In the former, variables are associated by means of a predictable pattern for a population, and in the latter, the specification of properties and profiles, which are subject to analysis, is sought (Hernández-Sampieri *et al*., 2014). To these ends, a quantitative analysis of elements of this nature in instrument-surveys pre- and post-test is carried out to measure the correlational levels between expectancy-value and achievement goals. Afterwards, a qualitative data analysis (QDA) is performed for a better understanding toward identifying the type of expectancy-value that tends to acquire high rates of achievement goals. IBM SPSS v. 25 software was used for quantitative analysis, while NVivo v. 12 was used for QDA.

The mixed method (quantitative and qualitative) increases the dimensions in the research project, in the sense that the understanding of the phenomenon is greater and deeper, since the results yield information that allows understanding the phenomenon beyond its size or dimension (Guetterman *et al*., 2017).

3.1. Application context

In 2015, México's National Council of Science and Technology (CONACYT, for its Spanish acronym), together with the Secretary of Energy (SENER, for its Spanish acronym) and Tecnológico de Monterrey, created an energy strategic initiative to develop proposals for energy reform and gathered several sectors of society, such as academics, business people, and communities. Later, this project would focus on the "Binational Laboratory for the Intelligent Management of Energy Sustainability and Technological Formation" (https://energialab.tec.mx/).

Within the framework of this macro-project, 12 MOOCs were created, the contents of which cover general topics such as energy saving, in addition to more complex issues such as Smart Grids. These academic activities were offered on both MexicoX (http://www.mexicox.gob.mx/) and edX (https://www.edx.org/school/tecnologico-de-monterrey) platforms from 16 January 2017 until 21 September 2018. A total of 123,124 participants were enrolled, 16,887 of whom successfully completed the course, with an overall completion rate of 13.715% (Table I), which is higher than the common denominator of 5% to 8% noted by Osuna-Acedo *et al*. (2018).

These MOOCs follow the traditional instructional design of xMOOCs, which are very similar to traditional e-learning courses, in which the content is presented in a structural manner, which have a start and end date and the assessments of which are focussed on multiple choice tests or co-assessment exercises (Admiraal, 2015; Daniel, 2012; Yousef *et al*., 2015). The 12 MOOCs on energy that are subject to this study are presented in the following table:

Table I. MOOCs on energy subject to this study

MOOC	*Number of enrollments* [*n*(e)]	*Number of students that finished the course* [*n* (f)]	Completion Rate [C_{R}]
Energy saving	12,929	2,019	15.616%
Electrical energy distribution	5,549	639	11.515%
Smart Grid: Future electrical networks	6,608	821	12.424%
Smart Grid: Technical fundamentals	5,498	743	13.514%
Electrical energy transmission	5,961	1,074	18.017%
Conventional clean energy and its technology	18,693	2,770	14.818%
Electrical energy: Concepts and principles	15,978	1,807	11.309%
Energy: Past, present, and future	13,224	2,106	15.925%
Carbon markets	6,710	910	13.561%
Energy markets	10,255	846	8.249%
The new electrical industry in México	8,975	1,224	13.637%
Energy reform and its opportunities	12,744	1,928	15.128%
TOTAL	***123,124***	**16,887**	**13.715%**

All the MOOCs mentioned (Table I) had two pre-determined surveys regarding expectancy-value and achievement goals, based on pre- and post-tests aiming to assess the participants' opinions on their motivations and whether they were fulfilled when completing the course.

The present study was carried out on the basis of these 12 courses because they were open educational resources that were developed within the framework of the aforementioned project, in which all had the same instructional design, more or less the same duration, similar subject matter and were located on the same platforms (edX and MexicoX), which allowed for some control over the profile of their participants. In addition, the MOOCs were set up in the midst of the energy reform in Mexico, which ensured that the population, and specifically professionals in the sector, were more interested in carrying out these learning activities.

3.2. Instrument

To collect information on several independent and dependent variables and co-variables on opinions before starting (pre-test) and after finishing (post-test) the MOOCs, two instrument-surveys were conducted using a link connected to the Survey Monkey® system. This data collection was carried out between October 1 and December 31, 2018, after all the MOOC editions had been completed.

The pre-test instrument consisted of 37 questions, 14 of which were related to independent variables (age, gender, level of education, job…); 8 were related to motivations and expectations;

5 were related to levels of technological skills; 5 were related to prior knowledge on the MOOC to be taken; and the remaining 5 were related to the tendency to participate in discussion forum. These questions combined the options of closed answers (simple and multiple selections), open answers (short text) and Likert scales. All questions and answers were in Spanish, which are translated into English for this paper. In the case of the Likert scales, 4 points were chosen (1-strongly disagree, 4-strongly agree), since neutral values were not desired. The related questions for measuring expectation-value and achievement goals were as follows:

- Why are you interested in enrolling in this course? [Free text response].
- What is your level of commitment to this course? [Free text response].
- I believe that this course will help meet the training needs that led me to enroll in it. [Response options in likert scale].
- I believe that this course will help to improve my professional development (current or future). [Response options in likert scale].
- I believe this course will improve my current or future business or employment opportunities. [Response options in likert scale].
- I think this course will make it easier for me to establish professional relationships with people who have interests similar to mine. [Response options in likert scale].
- I believe that this course will improve my academic formation. [Response options in likert scale].
- I believe I have the skills (study, use of ICT, etc.) necessary to successfully complete this course. [Response options in likert scale].

The pre-test dimensions were conclusive, both in terms of the validity of the construct, its content and reliability (see Table II) and the items produced significant figures in some of the four proposed variables. Only item 21 produced inflated figures in two dimensions, but given its theoretical justification and the highest value of Cronbach's alpha, it was kept in the creation of the construct. Exploratory Factorial Analysis (EFA) data: explained variance = 66.83%, *KMO* = 0.930, Bartlett's test for sphericity [X^2 (190) = 63854.763, $p < 0.001$]. Cronbach's alpha was high, above 0.84.

Table II. Analysis for the reliability of the pre-test instrument

	Motivations and expectancy-value (16-21)	Prior digital competencies (22-26)	Prior knowledge (27-31)	Intention to interact with classmates (32-35)
Eigen value	2.048	8.164	1.677	1.477
% Explained variance	10.24%	40.82%	8.38%	7.39%
Cronbach's alpha	0.861	0.890	0.847	0.872

On the other hand, the post-test instrument consisted of 30 questions: 5 questions on independent variables and pre-post interrelated co-variables; 6 questions on the dimension of achievement goals; 6 questions on usage criteria; 5 questions on knowledge acquired prior to the MOOC; and 8 questions on interactions in the discussion fora, in that order. The related questions for measuring expectation-value and achievement goals were as follows:

- This course satisfied the training needs that led me to enroll in it. [Response options in likert scale].
- After having taken it, I am convinced that this course will help to improve my professional development. [Response options in likert scale].

- Having taken it, I am convinced that this course will improve my business opportunities. [Response options in likert scale].
- I think this course made it easier for me to establish professional relationships with people who have similar interests to mine. [Response options in likert scale].
- I think this course improved my academic background. [Response options in likert scale].
- I believe that I have had sufficient perseverance to successfully complete this course. [Response options in likert scale].

The Exploratory Factorial Analysis (EFA) of the dimensions of the second survey turned out to be more problematic, but given the intention to compare constructs equivalent to the ones used in the first survey, and given the fact that Cronbach's alpha also produced high values, four constructs were created: i) course value (Cronbach's alpha: 0.842; items 4–10); ii) acquired digital competencies (Cronbach's alpha: 0.847; items 11 and 13–16); iii) acquired knowledge (Cronbach's alpha: 0.882; items 17–21); and iv) interaction with classmates (Cronbach's alpha: 0.871; items 23 and 25).

Once reliability was proven and the constructs were generated by means of the average of the corresponding items, the analysis was carried out. Pearson correlations and Student's *t*-test were mainly used for independent sampling.

For the qualitative analysis in this study, which seeks to establish expectancy-value profiles that tend to have a higher correlation with achievement goals, the QDA NVivo® programme *v. 11* pro was used. Code sets were grouped in the hermeneutic unit as follows:

Table III. Expectancy-value grouping by code sets

Code sets	Lexicons-type
Needs for training and professional development	Learn, train, teach
Personal development	Improve, know, expand, understand, help
Job/business opportunities	Employability, work, business, job opportunity
Professional relationships	Interrelate, meet people, networking, networks, equipment
Others	Curiosity, friends in the MOOC

3.3. Participants (pre- and post-test)

As shown in Table I, a total of 123,124 participants were enrolled in the 12 MOOCs (n_e), of which 35,040 voluntarily answered the initial survey and 16,887 of whom completed the courses (n_f) for a completion rate of 13.715%. Because correlation analysis can only be carried out depending on the number of participants who started and finished the course, it is understood that n_f is the population (16,887). After data cleansing and anonymization by deleting incorrect or inconsistent data, the total sampling for this study remains at a frequency (*f*) of 6,029 participants, which represents 35.70% of the population and is a sampling that considers a confidence interval of 95% and a margin of error of +/-5%. The demographic information of the total population studied is shown in the Table IV.

Table IV. Population demographic information

	n	%
Gender		
Male	22,689	64.751

Female	12,351	35.248
Age		
18-25	136	.388
26-35	21,321	60.847
36-45	13,456	38.401
46-65	118	.336
≥66	9	.025
Country		
Mexico	32,545	92.879
Colombia	605	1.726
Peru	380	1.084
Ecuador	257	.733
Other (Spanish speaking countries)	1,253	3.575
Maximun Level of Education		
Elementary education	728	2.077
Secondary education (High School)	14,592	41.643
University education completed	18,031	51.458
Master degree	1,191	3.398
PhD degree	498	1.421

4. Results

4.1. Correlation between expectancy-value and achievement goals

First, to fulfil the first objective of this research, measurements to determine the existence of the correlation between motivations and expectancy-value and achievement goals were performed, the results of which were significant [r(3891)= 0.449, p < 0.01] (see Figure 3), positive and between moderate and strong. The existing correlation between initial digital competencies and acquired knowledge was also significant [r(3825) = 0.353, p< 0.01], again positive and moderate. The same thing occurred when the correlation between acquired knowledge and starting knowledge was measured [r(3366) = 0.292, p < 0.01] and then, when the correlation between acquired knowledge and the initial intention to interact with classmates was measured [r(3965) = 0.368, p < 0.01].

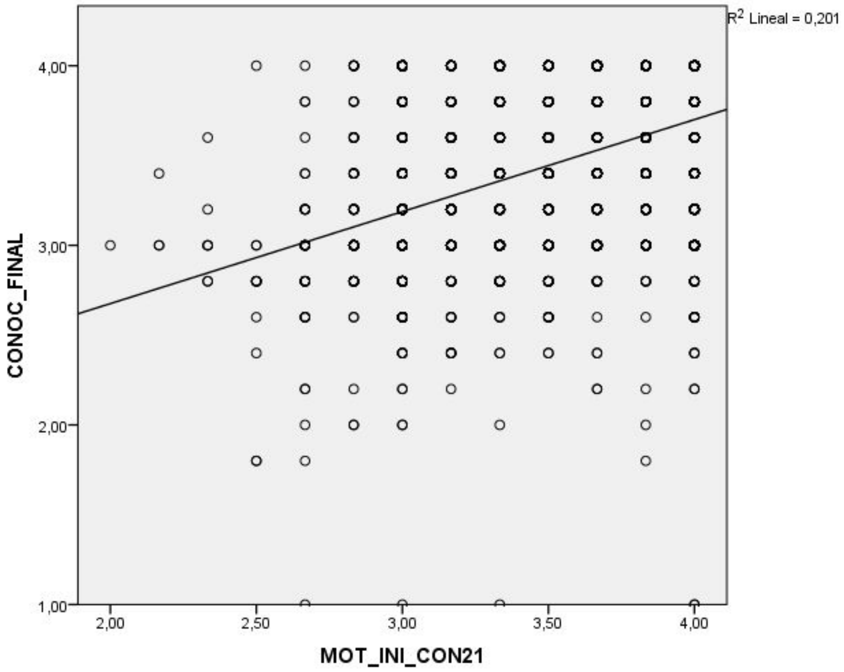


Figure 3. Existence of direct correlation between expectancy-value and achievement goals.
Note: The achievement goals were valued using the dimension 'the acquired knowledge fulfilled my expectations'.

To determine whether prior experiences with MOOCs affect the correlation between expectancy-value and achievement goals, such a correlation was proven for each of the possible answers. Thus, [r(507) = 0.469, p < 0.01] if they took three or more prior MOOCs; [r(264) = 0.454, p< 0.01] if they took two; [r(671) = 0.486, p < 0.01] if they took one; [r(364) = 0.337, p< 0.01] if they had enrolled in the past but did not complete it and [r(2092) = 0.437, p< 0.01] if they had never enrolled earlier (see Table V).

Table V. Correlation levels between expectancy-value and achievement goals

Correlations	*r*	*P*	Correlation
Expectancy-value and achievement goals	(3891) 0.449	< 0.01	Positive between moderate and strong
Initial digital competencies and acquired knowledge	(3825) 0.353	< 0.01	Positive and moderate
Acquired knowledge and starting knowledge	(3366) 0.292	< 0.01	Positive
Acquired knowledge and initial intention to interact with classmates	(3965) 0.368	< 0.01	Positive and moderate
Achievement goals and participation in 3 or more prior MOOCs	(507) 0.469	< 0.01	Positive and strong
Achievement goals and participation in 2 prior MOOCs	(264) 0.454	< 0.01	Positive between moderate and strong
Achievement goals and participation in 1 prior MOOC	(671) 0.486	< 0.01	Positive and strong
Achievement goals upon enrollment in a MOOC while never completing it	(364) 0.337	< 0.01	Positive and moderate

Achievement goals while never enrolling on a MOOC	(2092) 0.437	< 0.01	Positive between moderate and strong

Note: (*r*) Coefficient of Pearson correlation; (*p*) p-value in t-student.

From Table III, it can be said that the highest level of correlation between expectancy-value and achievement goals is present when the participant has previously taken an MOOC [r(671) = 0.486, p< 0.01], which is closely followed by those who have taken 3 or more MOOCs [r(507) = 0.469, p< 0.01], showing that prior experience in this type of learning modality reduces the gap between prospects (expectancy-value) and fulfilment (achievement goals). As shown in Figure 4, the lowest correlation appears in participants who had never completed an MOOC in which they had enrolled.

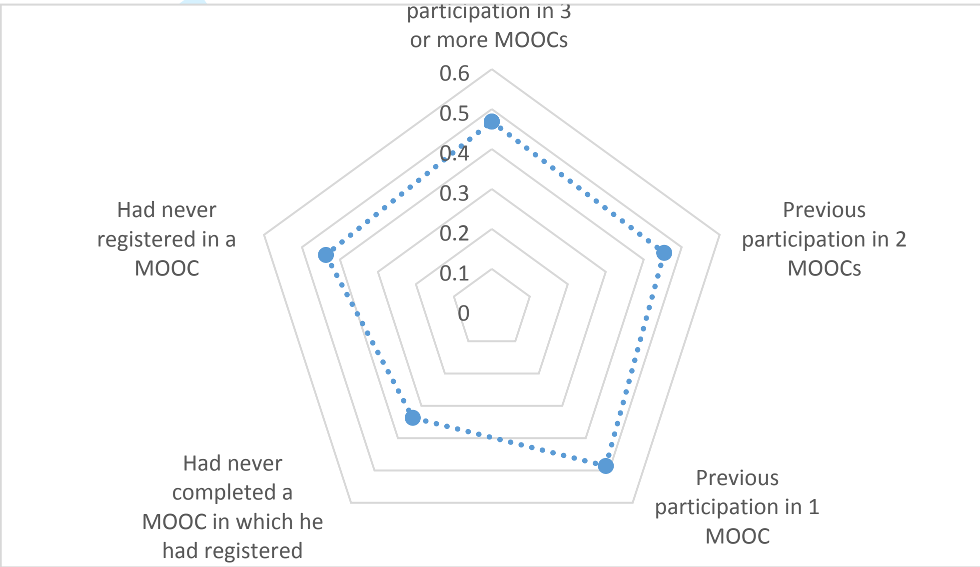


Figure 4. Relationship between experiences with MOOCs and correlation between expectancy-value and achievement goals

4.2. Expectancy-value typologies with a tendency to achieve goals

To fulfil the second objective of this paper, question number 15 of the pre-test related to 'Which of the following options better describe your interest in enrolling in this course?' (close and open options) was analyzed in relation to questions 6 to 10 of the post-test, related to the satisfaction of achievement goals (career development, job/business opportunities, professional relationships and academic training). Given that much of the information presented was in the open option (others), the grouping system by set of codes explained in Table III was used to carry out a QDA.

Participants with a higher tendency to achieve goals are those who enroll in the course because of work reasons (to obtain a promotion at work, to improve knowledge in the working field or to acquire a better job), with a frequency (f) of 2,562 participants (42.49%), followed by those who take the course due to personal-training development 1,547 (25.65%) and those who take it for job/business opportunities with a frequency (f) of 1,026 participants (17.01%). Conversely, 598 participants (9.91%) stated that the reason for taking MOOCs was to create professional contacts (networking), and only 296 participants stated that they took the course for other reasons, such as curiosity for MOOCs or because they had a friend taking the course.

4.3. Qualitative results

As explained in the instrument section, the first two questions in the data collection instrument were free text responses: 1) Why are you interested in enrolling in this course?, and, 2) What is your level of commitment to this course? The answers to these questions were extracted from the survey and analyzed with the QDA NVivo v.12 software to create code families within the hermeneutic unit. In this sense, the qualitative results become dimensions of quantitative analysis, which allows a greater exploration of the phenomenon.

Regarding the first question (Why are you interested in enrolling in this course?), six code families emerged: i) because of curiosity or to know what a MOOC is, ii) because I want to have contact with other students interested in the subject, iii) because I have friends in the course, iv) because the course is related to my academic program, v) because the course is related to my work, and vi) the skills and knowledge provided by the subject will help me get a better job.

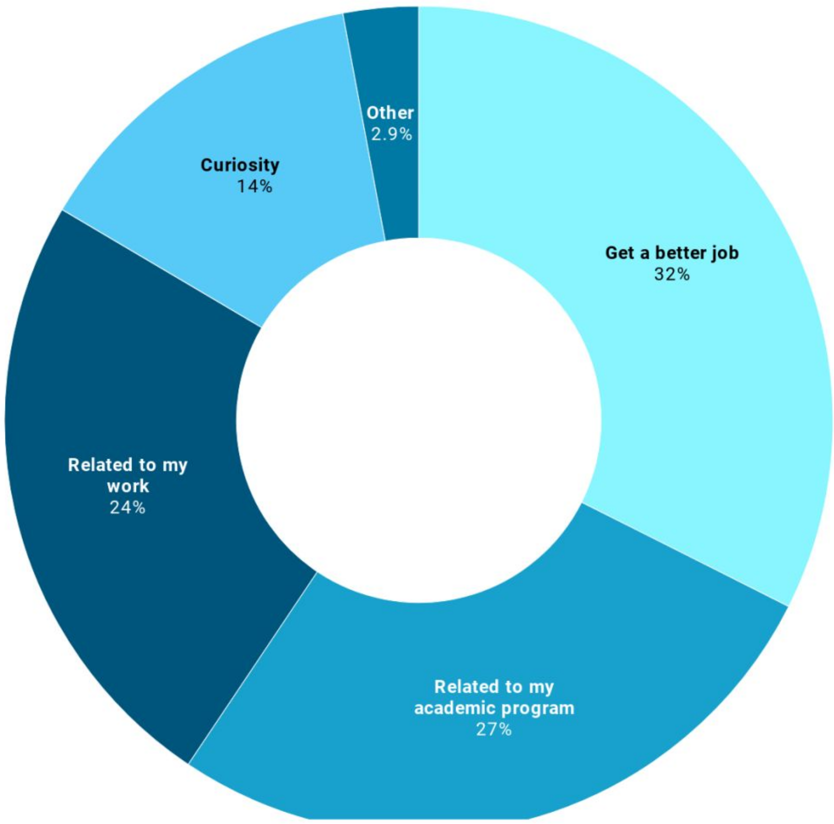


Figure 5. Reasons why participants signed up for MOOCs

As can be seen from Figure 5, most participants enrolled in the MOOCs for work reasons, either to get a better job (n=10301), or because the course subject was linked to their work (n=7656). Likewise, there is a great interest in studying MOOCs because they are related to academic programs that students are developing (both undergraduate and graduate studies) (n=8570), while curiosity (n=4312) is the fourth option. For emerging code families "because I want to have contact with other students interested in the subject" (n=757) and "because I have friends in the course" (n=176), appear as marginal results that do not succeed in collecting 3% of the answers.

Concerning the second question (What is your level of commitment to this course?), Five families of codes emerge from the qualitative analysis: i) I plan to do all the activities and complete the course because I am interested in the certificate, ii) I plan to do all the activities and complete the course even if I don't get the certificate, iii) I plan to do some activities and evaluations but I am not interested in finishing the course, iv) I am only interested in watching some videos and materials from the course and, v) I am interested in knowing what the course is about but I don't plan to watch the sessions or do the activities. The results were (Figure 6):

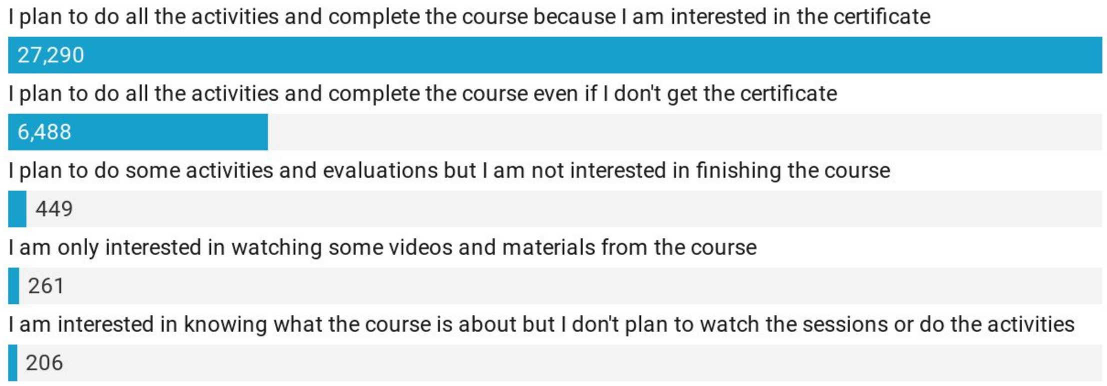


Figure 6. Level of commitment of participants to undertake the MOOC

5. Discussion and conclusion

Without doubt, MOOCs have been the subject of scientific interest ever since they were introduced in 2008 (Castaño *et al*., 2015). Their main critics have used MOOCs dropout rates, approximately 92% to 95% (Jordan, 2018; Osuna-Acedo *et al*., 2018), as an indicator of their educational inefficiency. However, this position has been discussed in several studies explaining that these educational activities should not be analyzed with the same perspective that is used to assess the effectiveness of traditional courses (for example, Kilgore *et al*., 2015; Kerr *et al*., 2015; Valdivia Vázquez et al., 2018; Liyanagunawardena *et al*., 2014). In the case of MOOCs, dropouts are more related to aspects of dissatisfaction, either over-learning personal objectives or failing to fulfil their expectancy-value.

In this regard, MOOCs should move away from the conventional model of master classes transformed into the digital and audiovisual environment, including activities and dynamics that allow the active participation of students, because as explained in previous studies (*v.gr.* Guajardo Leal, Navarro-Corona and Valenzuela González; Guajardo Leal and Valenzuela González, 2019; Romero-Rodríguez, Ramírez Montoya and Valenzuela González, 2019; 2020), educational innovation and innovative methods -such as gamification, simulations, project-based learning, among others- are often extrinsic motivators that allow participants to remain active subjects of learning.

This research work aims to determine the interrelation between expectancy-value and achievement goals in 12 MOOCs on energy sustainability to verify the existence of a direct correlation between both phenomena. By means of this analysis, it can be concluded that there is a positive correlation (between moderate and strong), from which it can be deduced that participants with a high rate of expectancy-value, that is, those who are certain that the course's content will be useful to them tend to persist, and to engage, which provides them with the motivation to reach and correlate the course with their achievement goals (personal/training, professional, or business and network related). These results are in line with those presented by Zheng *et al*. (2015) in that the decision to take a MOOC depends largely on current and future motivations (expectancy-value), and these results are also in keeping with those of Hew and Cheung (2014) and Littlejhon *et al*. (2016) to the extent that the main incentive is the acquisition of specific qualifications and practical skills instead of self-development or learning enjoyment elements.

Second, this paper aims to specify the types of declared expectancy-value that tend to keep a high degree of engagement, that is, the types of motivations that are prone to the successful completion of the courses. With regard to this, work motivation (promotion at work, improvement of knowledge in the work field, or acquisition of a better job) and personal-training development was shown to be 68.14% of the opinions ($\sum f = 4109$), while practically not considering 'curiosity for MOOCs' (4.90%) as a decisive factor of motivation to achievement as opposed to, in this sense, assertions by Zheng *et al*. (2015) and Hew and Cheung (2014).

On the other hand, this research validates intrinsic motivation of expectancy-value as emanating from a previous introspective analysis (acquired in the pre-test and confirmed in the post-test) in which the participants try to understand how the MOOC could be useful for them, particularly in the working and training aspects, supporting the assertions of Eccles and Wigfield (2002) and Wigfield and Eccles (2000) in that values, which are the reasons for enrolling in the MOOC, and beliefs of skills, which are the expectations of future success, directly influence performance (see Figure 2).

In conclusion, the profiles of participants in MOOCs with a higher tendency to successfully complete the course and with high rates of engagement include the following characteristics: i) previously succeeding in completing more than one MOOC [$r(671) = 0.486$, $p < 0.01$]; ii) taking an MOOC for work purposes (promotion, search for better job opportunities, etc.) [$f = 2562$] and iii) having intrinsic motivation, that is to say, not depending on external factors such as obligation and certifications. This information may be of interest to educational administrators, researchers, teachers, facilitators, and designers of learning environments. They could consider the findings when proposing designs for learning experiences and integrating resources, strategies or diagnostic and training assessments to explore these expectations in order to channel them into successful learning paths.

In relation to previous experience with MOOCs as a determinant of completion rates, it is agreed with Romero-Rodriguez, Ramirez Montoya and Valenzuela Gonzalez (2020) and Romero-Rodriguez, Ramirez-Montoya and Aguaded (2020) that this is closely related to levels of digital skills, understanding that for the realization of a MOOC is necessary a user-level digital literacy that in many cases is not sufficient in certain regions of the world. In this sense, the digital divide is a phenomenon that is narrowing with the new generations and, above all, with the expansion of Internet coverage, although it is still a pending issue in many countries.

In order to decrease dropout rates and increase the success of the MOOC's terminal rate, teachers and instructional designers can use the student profile information to make activity proposals or thematic approaches specific to the MOOC. Although in the pedagogical construction of any training activity the profile of the student body must be taken into consideration, there are MOOCs that due to their specialized characteristics - such as those analyzed in this research - are aimed at technical professionals, so the content must be adapted to their level and interests, as well as the teaching methodologies must seek the active participation of the student body to increase their motivation.

However, teachers and instructional designers usually know the student profiles once the teaching materials have been completed, the course designed and the registrations made, so it is essential to know the intended student profile before designing the MOOC. In this sense, there is no «standard model of MOOC», and it is necessary to adapt its instructional design to the specific experiences, expectations and motivations of each student profile.

Acknowledgements

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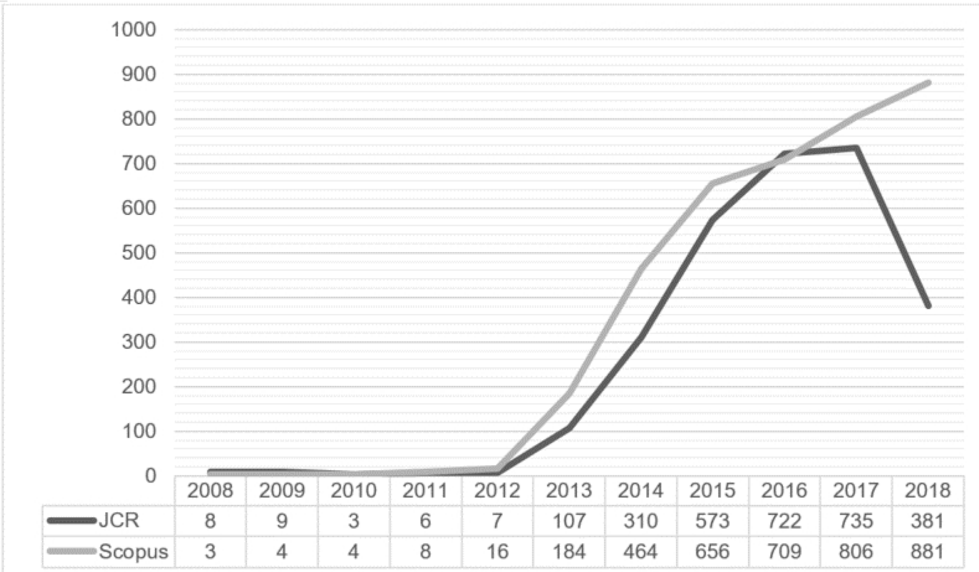
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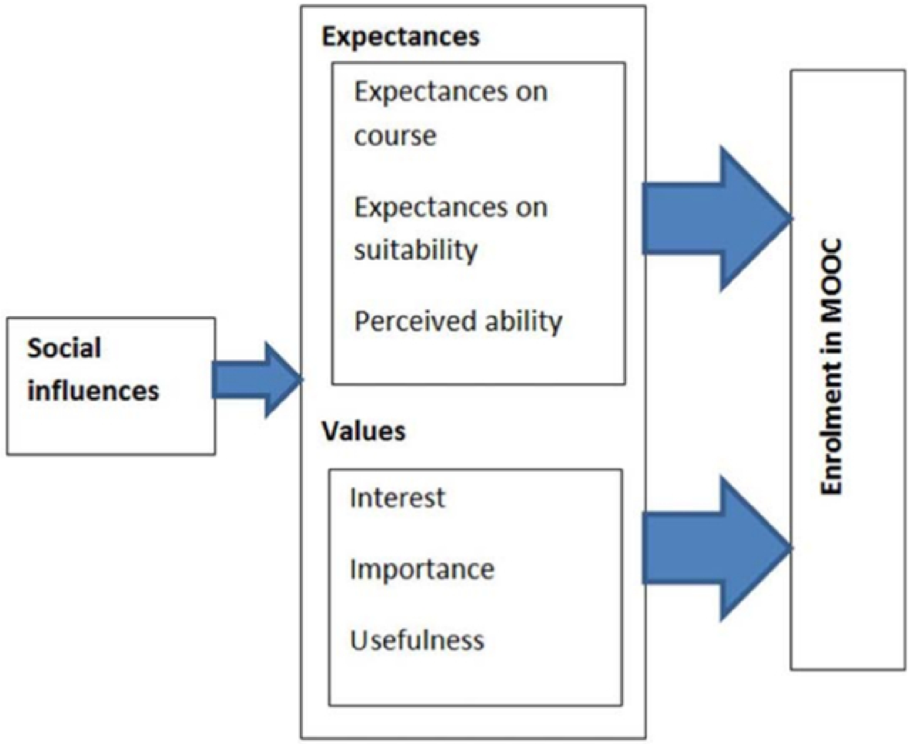
Figure 1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Expectances on course
Expectances on suitability
Perceived ability
Social influences
Values
Interest
Importance
Usefulness
Enrolment in MOOC

Figure 2.

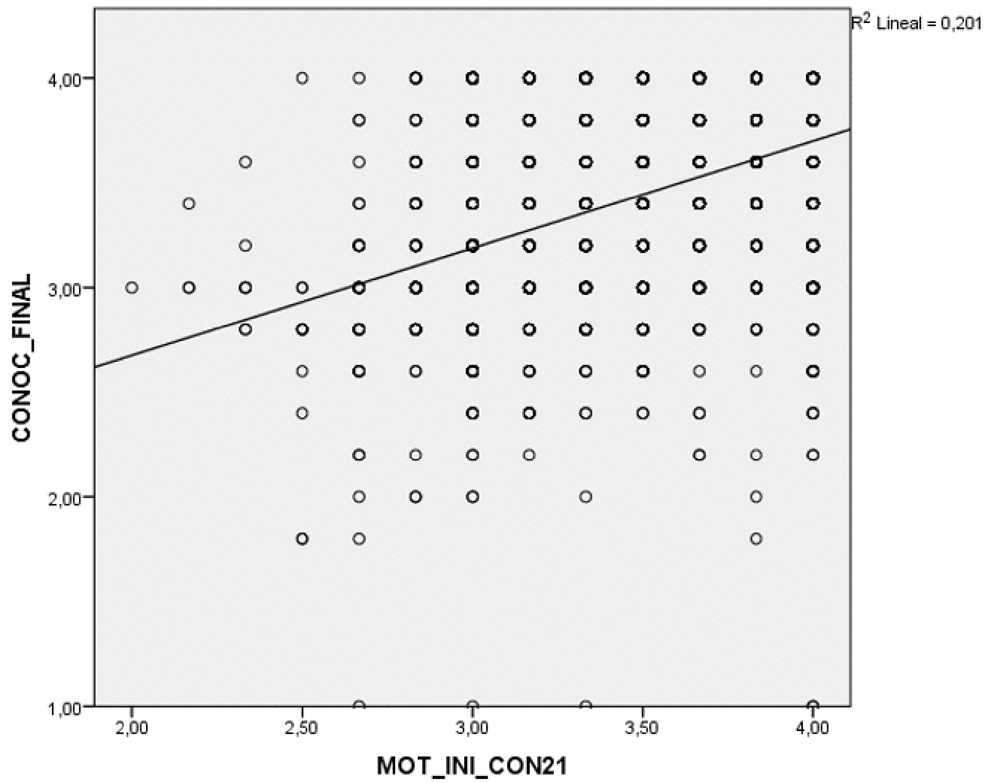
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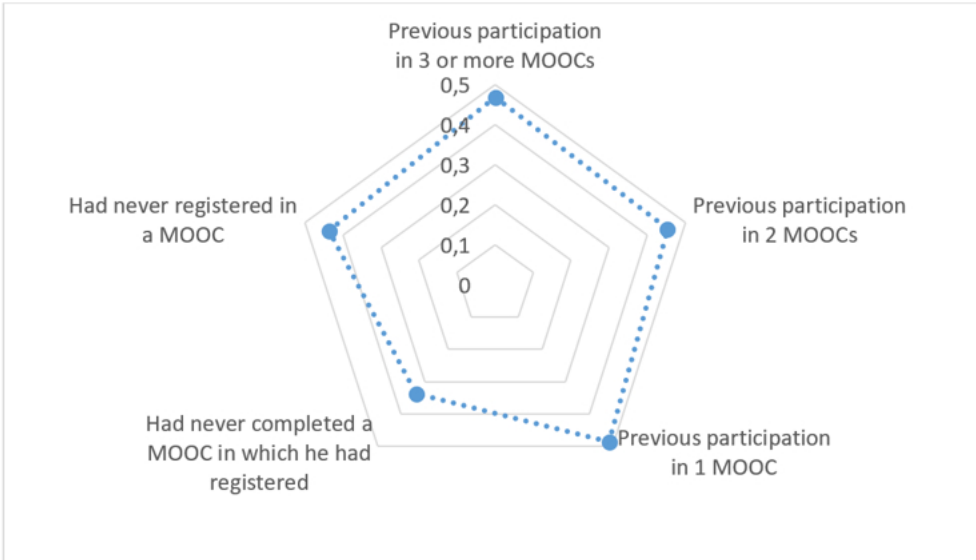
Figure 3.


Previous participation in 3 or more MOOCs
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Previous participation in 2 MOOCs
Previous participation in 1 MOOC
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Had never registered in a MOOC

Figure 4.

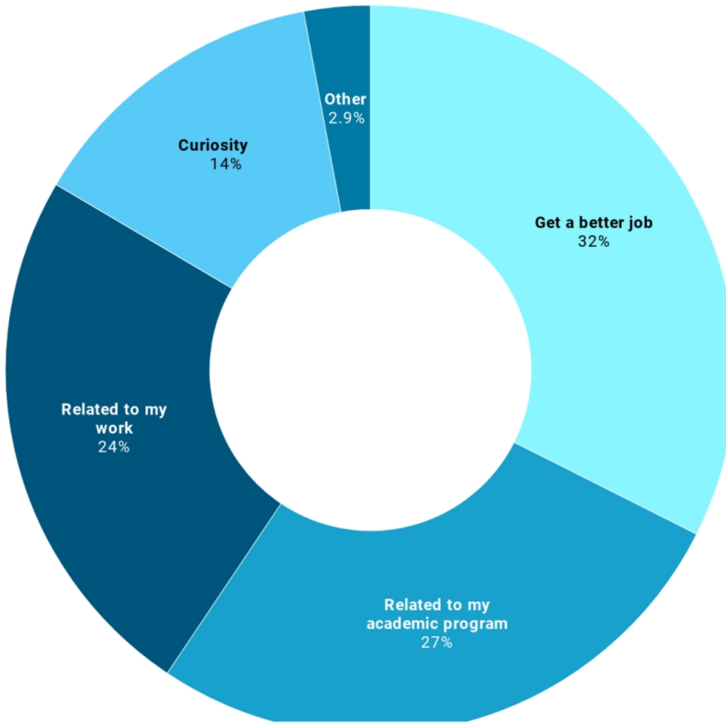

Figure 5.

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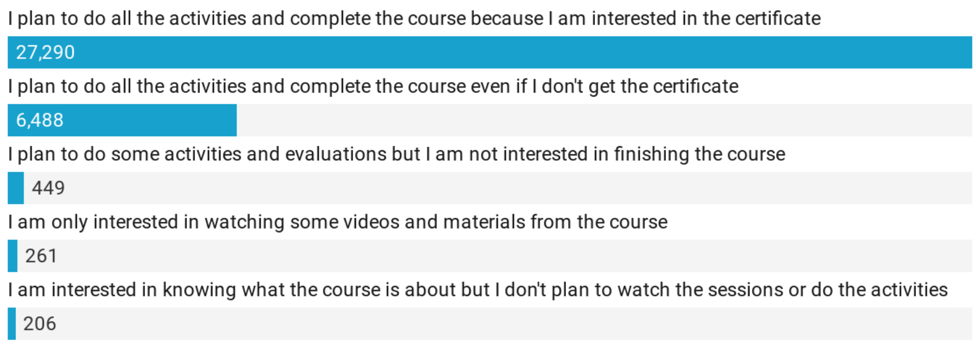

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Correlation analysis between expectancy-value and achievement goals in MOOCs on energy sustainability

Profiles with higher engagement

Abstract

Purpose – This research seeks to analyze the interrelationship that exists between expectancy-value and achievement goals as factors that are decisive for participants' higher engagement in 12 MOOCs on energy sustainability and to determine the profile of participants achieving higher success rates.

Design/methodology/approach – A qualitative–quantitative study of correlational and descriptive scope is carried out on two instruments based on pre- and post-tests of 6,029 participants, which is followed by a Qualitative Data Analysis (QDA) distributed by code families to identify participants' main motivations to take MOOCs.

Findings – The results showed a positive moderate-high correlation between expectancy-value and achievement goals, which means in a practical sense that the participants' subjective estimates of the possibility of reaching their goals prior to the beginning of the course were fulfilled, since the intentionality of the subjects-participants was positive with respect to the contents imparted.

Practical implications – The profiles of participants with a higher tendency to successfully finish the course and with high rates of engagement share the following characteristics: i) having previously and successfully finished more than one MOOC; ii) taking the MOOC for work purposes (promotion, seeking better job opportunities, etc.); and iii) having intrinsic motivation, that is, not depending on external factors such as obligations and certifications.

Originality/value – This research suggests that there are pre-educational factors that define the trend of successful completion of MOOCs, based on expectancy-value (e.g., previous experiences with other MOOCs) and achievement goals (e.g., job improvement), with external motivational issues such as completion certificates being less prevalent in the learning intention.

Keywords: E-Learning; Engagement; Motivation.

Paper type Research paper

1. Introduction

Ever since Massive Open Online Courses (MOOCs) were introduced in 2008, they have been very popular in the scientific and academic community because of their great versatility and the fact that they are a flexible educational alternative (Gabel, 2013). Thus, the popularity of MOOCs affects how universities deal with online training and even causes them to be regarded as the next development in e-learning (Castaño *et al.*, 2015).

This form of teaching gathers a large number of participants—sometimes hundreds of thousands in only one course—due to its universal accessibility, ubiquity, affordability (free), flexibility, and instructional design. Therefore, the enormous interest of the scientific community in these phenomena is not trivial. In fact, by means of an *ad hoc* analysis of the main international reference databases (Journal Citation Reports and Scopus), a total of 6,596 indexed documents have emerged since 2008 with a clear tendency to grow year-over-year (Figure 1).

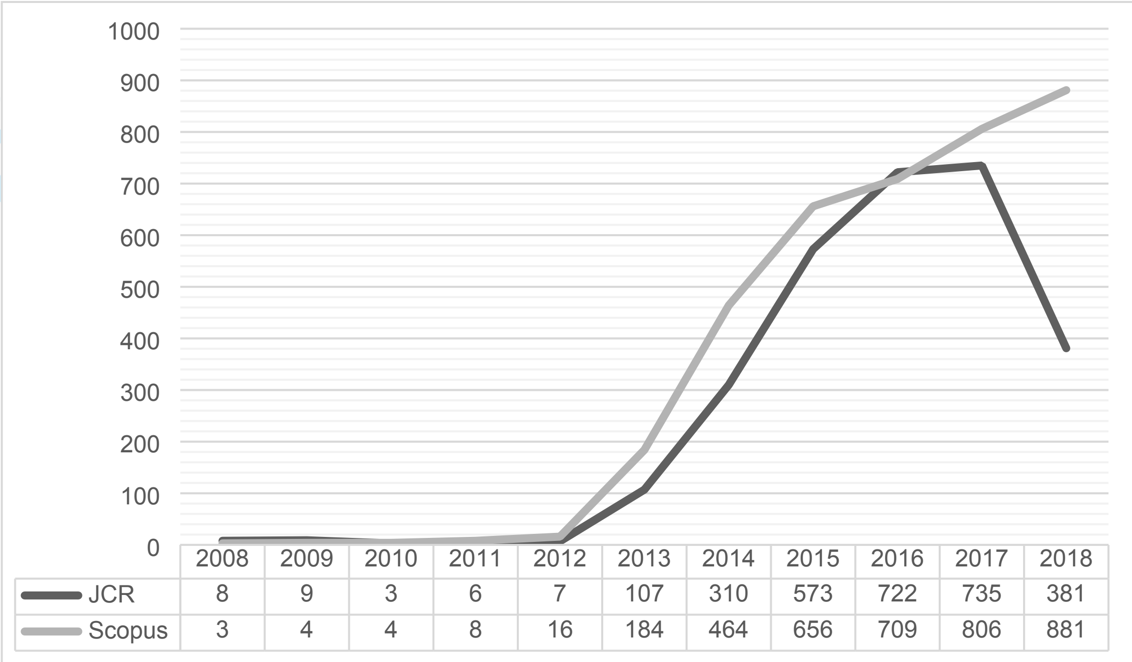

Figure 1. Publications on MOOCs in indexed JCR/Scopus journals

Note: The Boolean algorithm is used by subject (which includes title, abstract, and keywords) for the exploratory analysis of publications, which is limited to indexed journals from 2008 to 2018. At the time of the exploratory analysis (31/08/2019), not all the documents from 2018 were updated in the database, which could be the reason for the drop in the Journal Citation Reports® 2018.

From this initial exploratory analysis, we can agree with Castaño *et al*. (2015) that a great many emerging lines of research on MOOCs have focussed on the pedagogical and instructional design; interactions among participants; learning perspectives and dimensions, such as motivation and attitudes; and the emerging problem of high dropout rates of students.

On this specific matter, after analyzing 24 MOOCs, Jordan (2013) concludes that the highest completion rate was 19.2%, whereas average graduation rates failed to reach 10% of the starting participants. In another study carried out by the same researcher (Jordan, 2015), a similar completion rate is reasserted (0.7–52.1%, with an average of 12.6%). However, although this aspect remains a topic of academic discussion (for example, Kilgore *et al*., 2015; Kerr *et al*., 2015; Valdivia Vázquez *et al*., 2018; Beltrán Hernández de Galindo, Romero-Rodríguez and Ramírez Montoya, 2019), Liyanagunawardena *et al*. (2014) explain that MOOC students challenge the traditional notion of dropout because with the free and open nature of these courses, dropouts are more related to aspects of dissatisfaction, whether over personal learning goals or failure to fulfil their value expectations. Therefore, the free and asynchronous nature of these courses means that dropouts are not related to external factors (economy or time-related).

Motivations to take a MOOC as opposed to traditional courses are more variable (Kizilcec *et al*., 2013; Milligan *et al*., 2016; Terras and Ramsay, 2016). Traditional courses have a higher component of externally associated motivation (for example to obtain a certificate), whereas MOOC participants' motivations tend to be more intrinsic, such as interest in the topic covered in the course (Bonk *et al*., 2015; de Barba *et al*., 2016; Torres-Toukoumidis *et al*., 2018; Romero-Rodríguez, Ramírez-Montoya and Valenzuela González, 2019), a relationship with their environment of professional development and self-determination and challenge (Barak *et al*., 2016).

Studies such as the one by Zhou (2016) show that the decision to enrol in a MOOC depends largely on how participants see themselves, that is, the methods they employ to assess their preexisting knowledge on the subject, the time available to devote to the course, their resources and digital competencies, and their self-discipline abilities. On the other hand, White *et al*. (2014) explain that the three main reasons for choosing a MOOC are as follows: the fact that they are free, the desire to stay up-to-date with regard to knowledge, and interest in the subject, in that order. Through a series of interviews, Zheng *et al*. (2015) identify four types of motivations to enrol in a MOOC: to satisfy current needs, to prepare for the future (which includes obtaining a certificate), to satisfy a curiosity, and to meet people related to their field of study.

In this sense, Hew and Cheung (2014) mention four other motivational reasons as an incentive to enrol in a MOOC: to enhance or develop knowledge in a specific field, to satisfy curiosity regarding MOOCs, to overcome a personal challenge, and to acquire a qualification. On the other hand, Littlejhon *et al*. (2016) list the importance of the course content in connection with the following aspects of a participant's job: career development, increasing practical abilities, learning enjoyment, and professional growth. In view of the abovementioned reasons, it can be said that there are both extrinsic and intrinsic motivations although only the former are more important in the process of deciding whether to enrol.

2. Intrinsic motivation, expectancy-value and achievement goals

According to the scientific literature, it can be deduced that analyzing graduates from MOOCs has become a common strategy to assess participants' performance (Valdivia Vázquez *et al*., 2018), and with this, fundamentally, motivation has been proven to be a basic predictor to achieve a higher level of engagement (Pursel *et al*., 2016; Xu and Yang, 2016; Shapiro *et al*., 2017).

Motivation is defined by Colman (2016, p. 251) as a 'driving force responsible for the commencement, persistence, direction and vigour of the behaviour addressed toward a goal', while motivation to learn is defined as 'students' desire to learn about the learning materials' (Colquitt *et al*., 2002, p. 679). Naturally, motivation is a hyper-complex and dynamic aspect, in which elements such as interests, achievement goals, system of values and beliefs, self-effectiveness and control coexist (Ryan and Deci, 2000; Torres-Toukoumidis *et al*., 2016). These elements tend to change because of the learning environment, the contents or interactions of the course and more specifically in the MOOCs (de Barba *et al*., 2016).

There are several theoretical perspectives regarding motivation, with the most common one among them being self-determination as propounded by Ryan and Deci (2000), who explain that motivation is higher when it is intrinsic, that is to say, when an attitude or behaviour is present because of free will, pleasure, personal satisfaction, and the need to acquire competencies, all related to the need for self-development.

According to another theory, the one on achievement goals, students pursue goals in two dimensions when learning—control versus performance and focus versus avoidance (Elliot and McGregor, 2001)—which affect how students respond to achievement situations, choose which learning strategies to use and how they face academic challenges.

A third theory, which is the one on expectancy-value, explains that motivation comes from an introspective analysis that students make to understand how learning or an academic task may be useful to them (Eccles and Wigfield, 2002). This way, students should have a proactive and positive attitude toward content that according to this analysis they find interesting—such as future prospects—while this motivation should not be present for content that is unappealing to them. With regard to this, it is important to mention that some researchers (for example, Eccles and Wigfield, 2002; Wigfield and Eccles, 2000) understand that values (such as reasons to enrol in a MOOC) and beliefs of skills (prospective for future success) directly affect performance and persistence in any activity (Figure 2).

It is necessary to point out that the three theories mentioned are not exclusive to each other, having been extensively used as a basis for research on MOOCs (Plante *et al*., 2013), considering that involvement in this type of educational model is voluntary—hence the greater dependence on intrinsic motivation—and that completion essentially depends on participants keeping a good level of engagement during the course (Wigfield and Eccles, 2000).

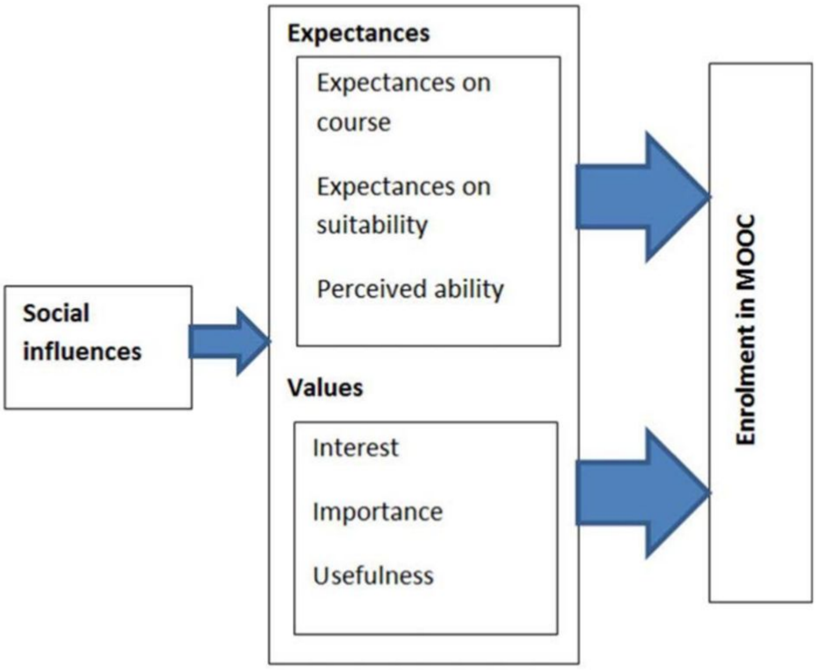

Figure 2. Expectancy-value factors and achievement goals that affect enrollment in a MOOC. Source: Luik *et al*. (2017, p. 158)

As shown in Figure 2, MOOC participants are socially influenced, that is to say, a set of stimuli govern their behaviour and motivations, for example, the emerging need to learn a specific skill (e.g., how to design a website). In this case, participants begin to search for learning environments according to their abilities and interests—time, budget, and preferences. The decision to enrol in a MOOC is made according to expectancy-value and achievement goals, by means of expectations (on the course and its learning materials, on the skills to be acquired and on the comparison between prior knowledge and level of knowledge to be acquired in the MOOC); values, that is, interest in the subject; the importance of the subject for personal and professional development and present and future usefulness of this knowledge (García Espinosa *et al*., 2015; Osuna-Acedo *et al*., 2018).

To this end, participants should establish, prior to taking a MOOC, their motivations and expectancy-value for taking the course, to correctly correlate dropout or fulfilment of achievement goals once the course is completed (Esposito, 2012). Only by gathering this information will it be possible to understand which expectancy-value profile (both on expectations and values) tend to have higher engagement with this teaching/learning method.

According to the foregoing discussion, this paper aims to determine the interrelationship between expectancy-value and achievement goals in MOOCs by means of an exploratory factorial and correlational analysis in courses on energy sustainability in order to verify that (*h0*) there is a direct correlation between both phenomena. The paper also aims to identify the most concurrent expected motivations and usefulness of the courses (expectancy-value) for participants who successfully complete MOOCs in comparison with the achievement goals obtained after completion.

This paper intends to verify that participants with a high rate of expectancy-value—those who have clarity regarding how a specific MOOC could be useful for them—tend to persist (fundamental in engagement)—in order to fulfil achievement goals, that is, to meet their post-course expectations. In addition, the type of expectancy-value (career development, job or business opportunities, academic training, and extended professional relationships, among others) that is most frequent in those completing the course should be determined.

3. Materials and methods

This paper uses a mixed design, with quantitative and qualitative variables for a correlational and descriptive analysis. In the former, variables are associated by means of a predictable pattern for a population, and in the latter, the specification of properties and profiles, which are subject to analysis, is sought (Hernández-Sampieri *et al*., 2014). To these ends, a quantitative analysis of elements of this nature in instrument-surveys pre- and post-test is carried out to measure the correlational levels between expectancy-value and achievement goals. Afterwards, a qualitative data analysis (QDA) is performed for a better understanding toward identifying the type of expectancy-value that tends to acquire high rates of achievement goals.

3.1. Application context

In 2015, México's National Council of Science and Technology (CONACYT, for its Spanish acronym), together with the Secretary of Energy (SENER, for its Spanish acronym) and Tecnológico de Monterrey, created an energy strategic initiative to develop proposals for energy reform and gathered several sectors of society, such as academics, business people, and communities. Later, this project would focus on the "Binational Laboratory for the Intelligent Management of Energy Sustainability and Technological Formation" (https://energialab.tec.mx/).

Within the framework of this macro-project, 12 MOOCs were created, the contents of which cover general topics such as energy saving, in addition to more complex issues such as Smart Grids. These academic activities were offered on both MexicoX (http://www.mexicox.gob.mx/) and edX (https://www.edx.org/school/tecnologico-de-monterrey) platforms from 16 January 2017 until 21 September 2018. A total of 123,124 participants were enrolled, 16,887 of whom successfully completed the course, with an overall completion rate of 13.715% (Table I), which is higher than the common denominator of 5% to 8% noted by Osuna-Acedo *et al*. (2018).

These MOOCs follow the traditional instructional design of xMOOCs, which are very similar to traditional e-learning courses, in which the content is presented in a structural manner, which have a start and end date and the assessments of which are focussed on multiple choice tests or co-assessment exercises (Admiraal, 2015; Daniel, 2012; Yousef *et al*., 2015). The 12 MOOCs on energy that are subject to this study are presented in the following table:

Table I. MOOCs on energy subject to this study

MOOC	***Number of enrollments* [*n*(e)]**	***Number of students that finished the course* [*n* (f)]**	**Completion Rate [$C_{R]}$**
Energy saving	12,929	2,019	15.616%
Electrical energy distribution	5,549	639	11.515%
Smart Grid: Future electrical networks	6,608	821	12.424%

Smart Grid: Technical fundamentals	5,498	743	13.514%
Electrical energy transmission	5,961	1,074	18.017%
Conventional clean energy and its technology	18,693	2,770	14.818%
Electrical energy: Concepts and principles	15,978	1,807	11.309%
Energy: Past, present, and future	13,224	2,106	15.925%
Carbon markets	6,710	910	13.561%
Energy markets	10,255	846	8.249%
The new electrical industry in México	8,975	1,224	13.637%
Energy reform and its opportunities	12,744	1,928	15.128%
TOTAL	***123,124***	**16,887**	**13.715%**

All the MOOCs mentioned (Table I) had two pre-determined surveys regarding expectancy-value and achievement goals, based on pre- and post-tests aiming to assess the participants' opinions on their motivations and whether they were fulfilled when completing the course.

3.2. Instrument

To collect information on several independent and dependent variables and co-variables on opinions before starting (pre-test) and after finishing (post-test) the MOOCs, two instrument-surveys were conducted using a link connected to the Survey Monkey® system.

The pre-test instrument consisted of 37 questions, 14 of which were related to independent variables (age, gender, level of education, job…); 8 were related to motivations and expectations; 5 were related to levels of technological skills; 5 were related to prior knowledge on the MOOC to be taken; and the remaining 5 were related to the tendency to participate in discussion fora. These questions combined the options of closed answers (simple and multiple selections), open answers (short text) and Likert scales. The related questions for measuring expectation-value and achievement goals were as follows:

- Which of the following best describes your interest in enrolling in this course? [Free text response].
- What is your level of commitment to this course? [Free text response].
- I believe that this course will help meet the training needs that led me to enroll in it. [Response options in likert scale].
- I believe that this course will help to improve my professional development (current or future). [Response options in likert scale].
- I believe this course will improve my current or future business or employment opportunities. [Response options in likert scale].
- I think this course will make it easier for me to establish professional relationships with people who have interests similar to mine. [Response options in likert scale].
- I believe that this course will improve my academic formation. [Response options in likert scale].
- I believe I have the skills (study, use of ICT, etc.) necessary to successfully complete this course. [Response options in likert scale].

The pre-test dimensions were conclusive, both in terms of the validity of the construct, its content and reliability (see Table II) and the items produced significant figures in some of the four proposed variables. Only item 21 produced inflated figures in two dimensions, but given its theoretical justification and the highest value of Cronbach's alpha, it was kept in the creation of the construct. Exploratory Factorial Analysis (EFA) data: explained variance = 66.83%, *KMO* = 0.930, Bartlett's test for sphericity [X^2 (190) = 63854.763, $p < 0.001$]. Cronbach's alpha was high, above 0.84.

Table II. Analysis for the reliability of the pre-test instrument

	Motivations and expectancy-value (16-21)	Prior digital competencies (22-26)	Prior knowledge (27-31)	Intention to interact with classmates (32-35)
Eigen value	2.048	8.164	1.677	1.477
% Explained variance	10.24%	40.82%	8.38%	7.39%
Cronbach's alpha	0.861	0.890	0.847	0.872

On the other hand, the post-test instrument consisted of 30 questions: 5 questions on independent variables and pre-post interrelated co-variables; 6 questions on the dimension of achievement goals; 6 questions on usage criteria; 5 questions on knowledge acquired prior to the MOOC; and 8 questions on interactions in the discussion fora, in that order. The related questions for measuring expectation-value and achievement goals were as follows:

- This course satisfied the training needs that led me to enroll in it. [Response options in likert scale].
- After having taken it, I am convinced that this course will help to improve my professional development. [Response options in likert scale].
- Having taken it, I am convinced that this course will improve my business opportunities. [Response options in likert scale].
- I think this course made it easier for me to establish professional relationships with people who have similar interests to mine. [Response options in likert scale].
- I think this course improved my academic background. [Response options in likert scale].
- I believe that I have had sufficient perseverance to successfully complete this course. [Response options in likert scale].

The Exploratory Factorial Analysis (EFA) of the dimensions of the second survey turned out to be more problematic, but given the intention to compare constructs equivalent to the ones used in the first survey, and given the fact that Cronbach's alpha also produced high values, four constructs were created: i) course value (Cronbach's alpha: 0.842; items 4–10); ii) acquired digital competencies (Cronbach's alpha: 0.847; items 11 and 13–16); iii) acquired knowledge (Cronbach's alpha: 0.882; items 17–21); and iv) interaction with classmates (Cronbach's alpha: 0.871; items 23 and 25).

Once reliability was proven and the constructs were generated by means of the average of the corresponding items, the analysis was carried out. Pearson correlations and Student's *t*-test were mainly used for independent sampling.

For the qualitative analysis in this study, which seeks to establish expectancy-value profiles that tend to have a higher correlation with achievement goals, the QDA NVivo® programme *v. 11* pro was used. Code sets were grouped in the hermeneutic unit as follows:

Table III. Expectancy-value grouping by code sets

Code sets	Lexicons-type
Needs for training and professional development	Learn, train, teach
Personal development	Improve, know, expand, understand, help

Job/business opportunities	Employability, work, business, job opportunity
Professional relationships	Interrelate, meet people, networking, networks, equipment
Others	Curiosity, friends in the MOOC

3.3. Participants (pre- and post-test)

As shown in Table I, a total of 123,124 participants were enrolled in the 12 MOOCs (n_e), of which 35,040 voluntarily answered the initial survey and 16,887 of whom completed the courses (n_f) for a completion rate of 13.715%. Because correlation analysis can only be carried out depending on the number of participants who started and finished the course, it is understood that n_f is the population (16,887). After data cleansing and anonymization by deleting incorrect or inconsistent data, the total sampling for this study remains at a frequency (*f*) of 6,029 participants, which represents 35.70% of the population and is a sampling that considers a confidence interval of 95% and a margin of error of +/-5%. The demographic information of the total population studied is shown in the Table IV.

Table IV. Population demographic information

	n	%
Gender		
Male	22,689	64.751
Female	12,351	35.248
Age		
18-25	136	.388
26-35	21,321	60.847
36-45	13,456	38.401
46-65	118	.336
≥66	9	.025
Country		
Mexico	32,545	92.879
Colombia	605	1.726
Peru	380	1.084
Ecuador	257	.733
Other (Spanish speaking countries)	1,253	3.575
Maximun Level of Education		
Elementary education	728	2.077
Secondary education (High School)	14,592	41.643
University education completed	18,031	51.458
Master degree	1,191	3.398
PhD degree	498	1.421

4. Results

4.1. Correlation between expectancy-value and achievement goals

First, to fulfil the first objective of this research, measurements to determine the existence of the correlation between motivations and expectancy-value and achievement goals were performed, the results of which were significant [r(3891)= 0.449, p < 0.01] (see Figure 3), positive and between moderate and strong. The existing correlation between initial digital competencies and acquired knowledge was also significant [r(3825) = 0.353, p< 0.01], again positive and moderate. The same thing occurred when the correlation between acquired knowledge and starting knowledge was measured [r(3366) = 0.292, p < 0.01] and then, when the correlation between acquired knowledge and the initial intention to interact with classmates was measured [r(3965) = 0.368, p < 0.01].

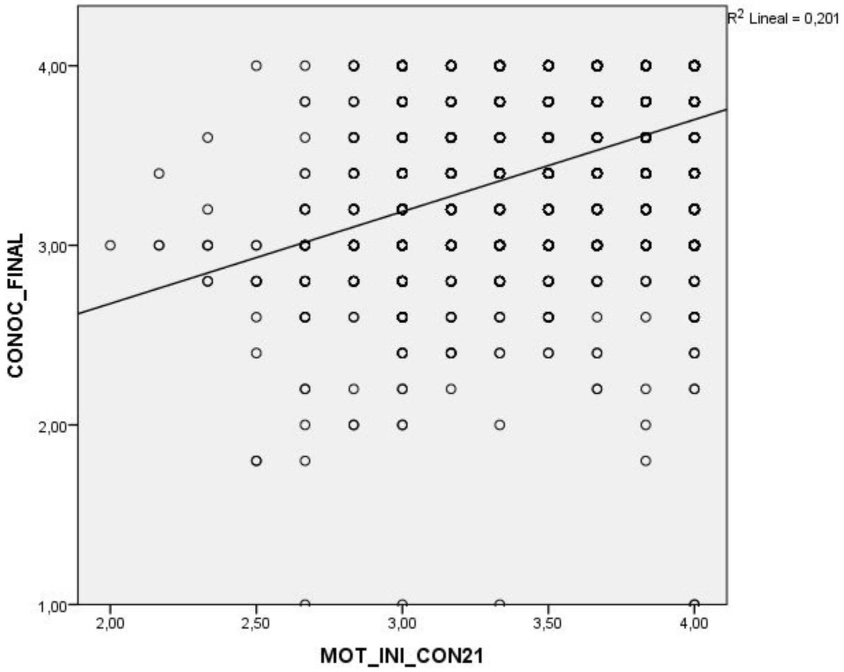

Figure 3. Existence of direct correlation between expectancy-value and achievement goals.
Note: The achievement goals were valued using the dimension 'the acquired knowledge fulfilled my expectations'.

To determine whether prior experiences with MOOCs affect the correlation between expectancy-value and achievement goals, such a correlation was proven for each of the possible answers. Thus, [r(507) = 0.469, p < 0.01] if they took three or more prior MOOCs; [r(264) = 0.454, p< 0.01] if they took two; [r(671) = 0.486, p < 0.01] if they took one; [r(364) = 0.337, p< 0.01] if they had enrolled in the past but did not complete it and [r(2092) = 0.437, p< 0.01] if they had never enrolled earlier (see Table V).

Table V. Correlation levels between expectancy-value and achievement goals

Correlations	*r*	*P*	Correlation
Expectancy-value and achievement goals	(3891) 0.449	< 0.01	Positive between moderate and strong
Initial digital competencies and acquired knowledge	(3825) 0.353	< 0.01	Positive and moderate
Acquired knowledge and starting knowledge	(3366) 0.292	< 0.01	Positive

Acquired knowledge and initial intention to interact with classmates	(3965) 0.368	< 0.01	Positive and moderate
Achievement goals and participation in 3 or more prior MOOCs	(507) 0.469	< 0.01	Positive and strong
Achievement goals and participation in 2 prior MOOCs	(264) 0.454	< 0.01	Positive between moderate and strong
Achievement goals and participation in 1 prior MOOC	(671) 0.486	< 0.01	Positive and strong
Achievement goals upon enrollment in a MOOC while never completing it	(364) 0.337	< 0.01	Positive and moderate
Achievement goals while never enrolling on a MOOC	(2092) 0.437	< 0.01	Positive between moderate and strong

Note: (*r*) Coefficient of Pearson correlation; (*p*) p-value in t-student.

From Table III, it can be said that the highest level of correlation between expectancy-value and achievement goals is present when the participant has previously taken an MOOC [r(671) = 0.486, $p< 0.01$], which is closely followed by those who have taken 3 or more MOOCs [r(507) = 0.469, $p< 0.01$], showing that prior experience in this type of learning modality reduces the gap between prospects (expectancy-value) and fulfilment (achievement goals). As shown in Figure 4, the lowest correlation appears in participants who had never completed an MOOC in which they had enrolled.

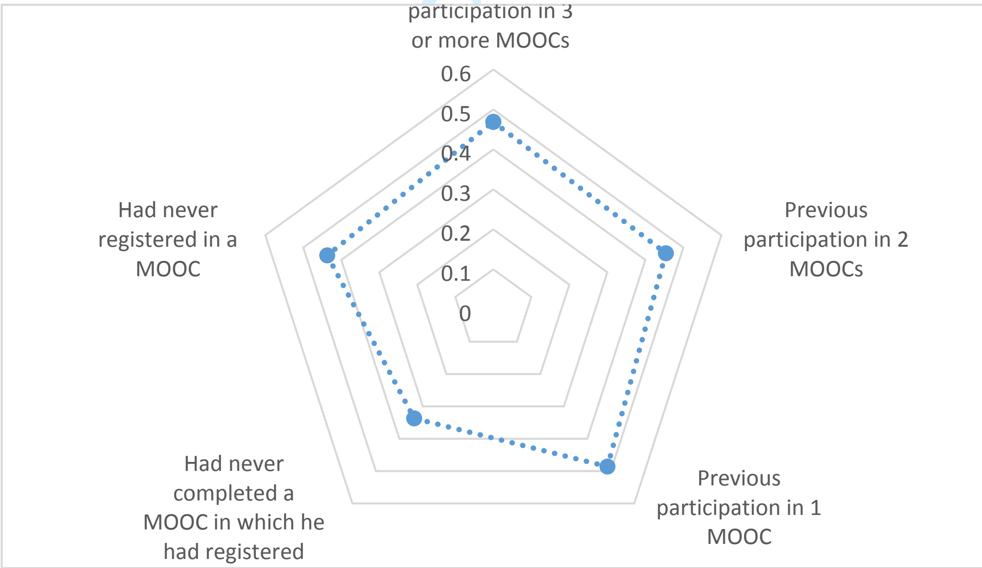

Figure 4. Relationship between experiences with MOOCs and correlation between expectancy-value and achievement goals

4.2. Expectancy-value typologies with a tendency to achieve goals

To fulfil the second objective of this paper, question number 15 of the pre-test related to 'Which of the following options better describe your interest in enrolling in this course?' (close and open options) was analyzed in relation to questions 6 to 10 of the post-test, related to the satisfaction of achievement goals (career development, job/business opportunities, professional relationships and academic training). Given that much of the information presented was in the open option (others), the grouping system by set of codes explained in Table III was used to carry out a QDA.

Participants with a higher tendency to achieve goals are those who enrol in the course because of work reasons (to obtain a promotion at work, to improve knowledge in the working field or to acquire a better job), with a frequency (*f*) of 2,562 participants (42.49%), followed by those who take the course due to personal-training development 1,547 (25.65%) and those who take it for job/business opportunities with a frequency (*f*) of 1,026 participants (17.01%). Conversely, 598 participants (9.91%) stated that the reason for taking MOOCs was to create professional contacts (networking), and only 296 participants stated that they took the course for other reasons, such as curiosity for MOOCs or because they had a friend taking the course.

5. Discussion and conclusion

Without doubt, MOOCs have been the subject of scientific interest ever since they were introduced in 2008 (Castaño *et al*., 2015). Their main critics have used MOOCs dropout rates, approximately 92% to 95% (Jordan, 2018; Osuna-Acedo *et al*., 2018), as an indicator of their educational inefficiency. However, this position has been discussed in several studies explaining that these educational activities should not be analyzed with the same perspective that is used to assess the effectiveness of traditional courses (for example, Kilgore *et al*., 2015; Kerr *et al*., 2015; Valdivia Vázquez et al., 2018; Liyanagunawardena *et al*., 2014). In the case of MOOCs, dropouts are more related to aspects of dissatisfaction, either over-learning personal objectives or failing to fulfil their expectancy-value.

This research work aims to determine the interrelation between expectancy-value and achievement goals in 12 MOOCs on energy sustainability to verify the existence of a direct correlation between both phenomena. By means of this analysis, it can be concluded that there is a positive correlation (between moderate and strong), from which it can be deduced that participants with a high rate of expectancy-value, that is, those who are certain that the course's content will be useful to them tend to persist, and to engage, which provides them with the motivation to reach and correlate the course with their achievement goals (personal/training, professional, or business and network related). These results are in line with those presented by Zheng *et al*. (2015) in that the decision to take a MOOC depends largely on current and future motivations (expectancy-value), and these results are also in keeping with those of Hew and Cheung (2014) and Littlejhon *et al*. (2016) to the extent that the main incentive is the acquisition of specific qualifications and practical skills instead of self-development or learning enjoyment elements.

Second, this paper aims to specify the types of declared expectancy-value that tend to keep a high degree of engagement, that is, the types of motivations that are prone to the successful completion of the courses. With regard to this, work motivation (promotion at work, improvement of knowledge in the work field, or acquisition of a better job) and personal-training development was shown to be 68.14% of the opinions ($\sum f = 4109$), while practically not considering 'curiosity for MOOCs' (4.90%) as a decisive factor of motivation to achievement as opposed to, in this sense, assertions by Zheng *et al*. (2015) and Hew and Cheung (2014).

On the other hand, this research validates intrinsic motivation of expectancy-value as emanating from a previous introspective analysis (acquired in the pre-test and confirmed in the post-test) in which the participants try to understand how the MOOC could be useful for them, particularly in the working and training aspects, supporting the assertions of Eccles and Wigfield

(2002) and Wigfield and Eccles (2000) in that values, which are the reasons for enrolling in the MOOC, and beliefs of skills, which are the expectations of future success, directly influence performance (see Figure 2).

In conclusion, the profiles of participants in MOOCs with a higher tendency to successfully complete the course and with high rates of engagement include the following characteristics: i) previously succeeding in completing more than one MOOC [$r(671) = 0.486$, $p < 0.01$]; ii) taking an MOOC for work purposes (promotion, search for better job opportunities, etc.) [$f = 2562$] and iii) having intrinsic motivation, that is to say, not depending on external factors such as obligation and certifications. This information may be of interest to educational administrators, researchers, teachers, facilitators, and designers of learning environments. They could consider the findings when proposing designs for learning experiences and integrating resources, strategies or diagnostic and training assessments to explore these expectations in order to channel them into successful learning paths.

Acknowledgements

Deleted for Peer Review

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