Data Analytics for Predicting Dropout

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ABSTRACT

Massive open online courses (MOOCs) offer multiple advantages and vast training possibilities in diverse topics for millions of people worldwide to continue their education. However, dropout rates are high; thus, it is important to continue investigating the reasons for dropout to implement new and better strategies to increase course completions. The present study aimed to analyze the data of a MOOC class on energy sustainability to know why students drop out, identify causes, and predict dropouts in future courses. The method used was Knowledge Discovery in Databases to analyze association rules in the data. Using the Mexico X platform, an initial, validated survey instrument was applied to 1506 students enrolled in the MOOC course "Conventional Clean Energy and its Technology." The results indicated that association rules allowed identifying participants' behavior according to the type of responses with a determined confidence level. Also, the association rules were appropriate for working with a large amount of data. In the present case, results of up to 86% confidence were obtained based on the rules. This research can be of value to decision-makers, teachers, researchers, designers, and those interested in large-scale training environments.

CCS CONCEPTS

• **Social and professional topics**; • **User characteristics**; • **Cultural characteristics**;

KEYWORDS

Data analytics, MOOCs, attrition, motivation, online education, educational innovation, higher education

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1 INTRODUCTION

One of the innovations of the past decade has been the massive open online course (MOOC), which revolutionized several areas, especially education. Because online learning became one of the technological advances of the 21st century, MOOCs were able to become an innovative reality [1]. Although they emerged years before, in 2012, they began to flourish thanks to platforms such as Udacity and Coursera and the open platform EdX implemented by the Massachusetts Institute of Technology and Harvard University [2]. From the beginning, the advantages attributed to them included democratizing access to knowledge and content, affordability, ubiquity and heterogeneity [3], global reach, and unlimited participation by students of different ages, countries, and interests who learn, interact, and collaborate globally [4]. Analyzing MOOC characteristics, one cannot deny the potential glimpsed in their emergence. However, it is necessary to see what outcomes they have yielded because their application has not been entirely successful.

The results obtained over the years reveal some MOOC issues that are the subject of analysis by the academic community. Indeed, despite the enthusiasm generated by MOOCs, the high dropout rate is one of the serious problems [5]; only between 5% and 10% of those enrolled complete the courses. Although dropout may characterize the "dark side" of MOOCs, one must remember that thousands of people are trained [6].

Empowerment was a hopeful characteristic attributed to MOOCs. However, most people who take a MOOC are not from poor countries, nor are they women, so the discourse of empowerment is no longer relevant [7]. However, the expectations of value in the courses have acquired preponderance [8]. The emergence of MOOCs has brought with it great possibilities for training, but at the same time, scholars have highlighted particular concerns to be addressed.

The present study aims to analyze the factors that predict MOOC participants' dropout. We point out that a diversity of studies address the prediction of MOOC incompletions; however, the present work differs in that our research works with information starting with the initial course or events before the course. Thus, the participants' behavior is analyzed using data from the survey provided at the beginning of the course. Then, according to the type of response, we used association rules to identify which participants are potential dropouts. The objective was to analyze the data of a MOOC course on energy sustainability to know the reasons that led students to drop out and identify the causes to predict future dropouts.

2 CONCEPTUAL FRAMEWORK

MOOCs have become an essential resource offered by universities since their creation. According to predictions, MOOCs were going to generate significant changes in higher education, which is why many universities bet on them; however, their low pass and completion rates have been a disappointing factor since their emergence [9]. Several authors have dedicated their research to one of the primary concerns, disillusionment, as a principal factor of low completion rates [10]. However, MOOCs have achieved successes and are an exciting way of teaching and learning, when done correctly, considering criteria such as quality, low or no cost, and accessibility [11]. One can also ponder the pedagogical model of MOOCs, which should be based on a methodology that addresses the participants' characteristics and offers learning experiences in real contexts [12]. Thus, it is to be expected that MOOCs can provide multiple benefits.

Undoubtedly, within the studies carried out, the influence of MOOC participants' motivation on course completion has been of interest. Within the pedagogical design of MOOCs, the lines of interest for research are interactions and learning perspectives, and within the latter, motivation, attitudes, and perspectives [13]. Motivation and digital skills have promoted student participation and are vital for their success [14]. In fact, Reparaz et al. [15] affirm that students with low motivation do not assume their roles and commit to the MOOC. On the other hand, when there is high motivation, students find it easy to participate in a MOOC [16]. Obviously, there is still a lot to discover about increasing motivation in MOOCs; however, we know that motivation is a critical factor in student performance and completion.

The social factor is distinctive in MOOC motivation. Participants are socially influenced through stimuli that determine their behavior and engagement [8]. It has been established that motivation is classifiable, i.e., related to the participant's video views and certifications; thus, learning activities reflect motivation levels [17]. Closely related to the above, MOOC participants see knowledge, work, convenience, and personal interest as the factors that motivate them in a course [18].

Although many elements promote motivation to pass a MOOC, in the present study, we aim to demonstrate how the participant's behavior can be predicted, a prediction closely associated with motivation and determined by the type of response selected to generate the rules.

The opposite of completion and motivation is failure and abandonment, which in MOOCs reaches high levels. Since their implementation, multiple publications have been written in this regard, where the common denominator is the incompletion rate. It has become crucial to solve the problems related to these rates because (even without exact figures) more and more students are repeating a MOOC course [19]. Therefore, identifying students who may fail is valuable because it predicts those who need help [20]. It is attrition that has led to implementing new strategies in MOOCs' methodology, design, and structure to achieve higher completion rates [21]. In addition, personal, family, social, work, and instructional factors influence enrollment and completion. For example, using a conventional design might be a primary reason for a low course completion rate [22].

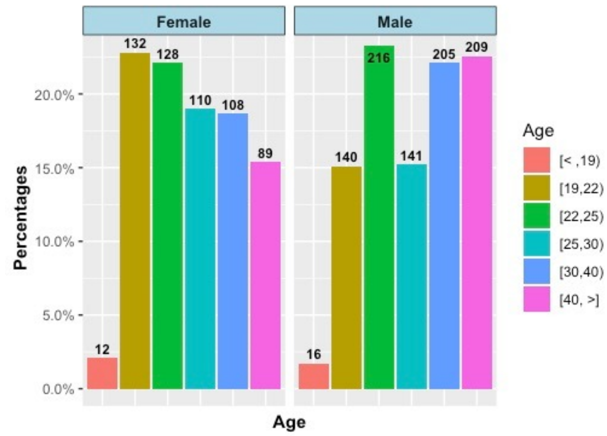

Figure 1: Gender and age of MOOC course participants

Based on these statements, it is interesting to know which MOOC course participant responses identify certain behaviors.

3 METHOD

The MOOC prediction models are many; there is a long list of options to implement prediction [23]. The method used in this research is Knowledge Discovery in Databases (KDD), justified by the current need to make sense of data and transform it into knowledge [24, 25]. The phases proposed in this methodology fit the process in this research:

- Understanding the domain.
- Creating a dataset.
- Cleaning and preprocessing.
- Data mining.
- Interpretation of results.
- Knowledge utilization.

3.1 Participants

We worked with a population of 1,506 MOOC participants who answered the initial survey for the course "Clean Conventional Energy and its Technology." There were 579 female participants and 927 males. In terms of age, among women, the ranges from 19 to 22 and 22 to 25 years old predominated, but the high numbers in the 25 to 30 and 30 to 40 years age are noteworthy. Among men, the ranges between 22 to 25 years and over 30 years old predominate, as shown in Figure 1

Figure 1 shows a clear interest in the topic of the MOOC by both the female and male populations. Although the age range is higher in some cases than in others, in general, we can observe in the distribution that the participants aged 19 to 40 demonstrated interest in energy sustainability as a subject of study and analysis by the population. This is not surprising because the topic is not limited to a particular sector or country but involves all society.

Regarding the level of education, most of the participants have a high school education and a bachelor's degree, i.e., an educated population.

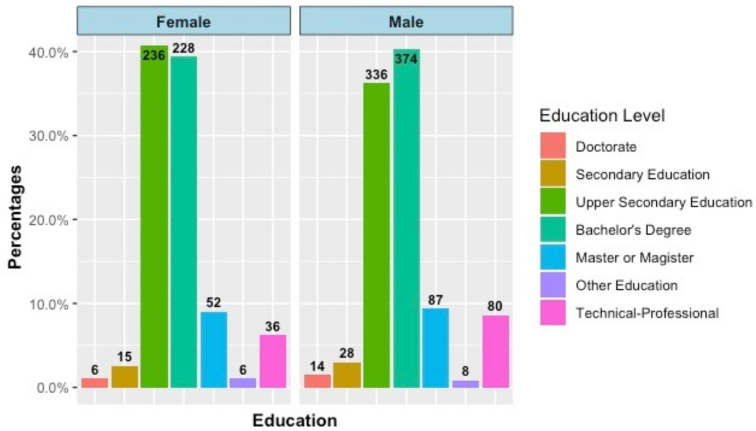

Figure 2: Education level of MOOC course participants

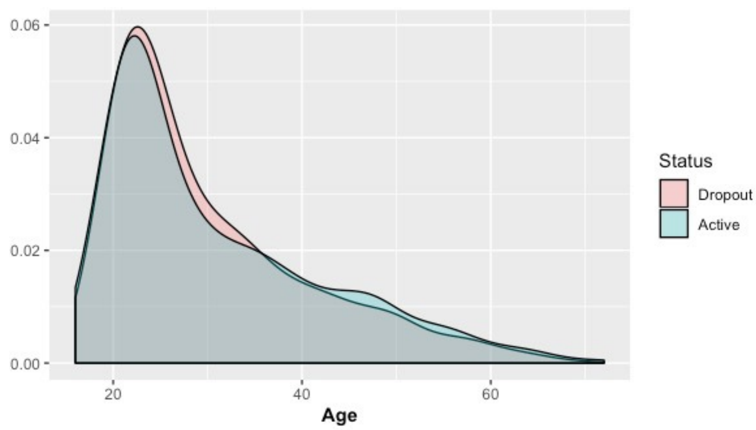

Figure 3: Distribution of the population sample who drop out and remain active.

Figure 2 shows that there is a greater interest in the subject matter of the study for those who have a high school and bachelor's degree level of education.

3.2 Instrument

The instrument used was the previously validated survey applied to all participants at the beginning of the course. This initial survey consisted of the following sections: identification data, interests, motivations for studying the MOOC, and previous knowledge [14]. It had 28 questions; some items required multiple-choice responses, and others were Likert scale questions with four response alternatives.

3.3 Procedure

The data from the initial survey was used. Although it was clear which students passed or failed the course based on their final grades, there were no criteria to define "FAIL" or "COMPLETE_COURSE," thus, it was necessary to define the criteria:

DROPOUT: Those students who did not take 50% of the exams (3 exams).

COMPLETE_COURSE: Students who took more than 50% of the exams (4, 5 or 6 exams).

Once the students were labeled " DROPOUT" or " COMPLETE_COURSE," we applied the "Apriori" algorithm in the "R" tool. We analyzed the results with the "Support" and "Confidence" metrics. Also, to validate the quality of the rules obtained, we obtained the "PASSED" students rate for each rule. Figure 3 shows that the data distribution for students who drop out and those who remain active is practically the same. It can also be seen that the highest number of students are between 20 and 25 years of age.

4 RESULTS

The "Apriori" algorithm generated 16 association rules. Table 1 shows the first ten, ordered according to the "Confidence" metric, i.e., the most significant rules. For example, in rule number 1, we see that its conditions (Antecedent and Consequent) are met in 49 records. These are cases in which the rule is met and represent 3.3% of the 1506 participants analyzed. This metric supports the rule and is shown in the "Support" column.

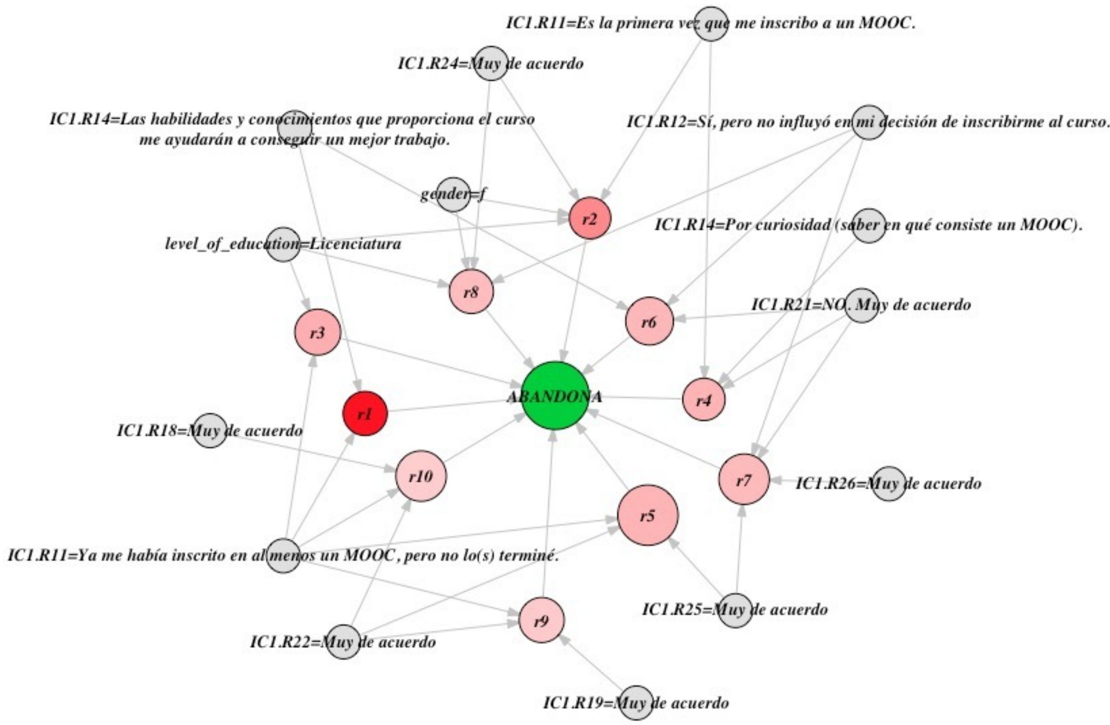

Figure 4: Rules generated based on the responses in the initial survey.

On the other hand, in rule number 1, 57 participants fulfilled only the Antecedent conditions, i.e., this set includes both students of the "DROPOUT" and the "COMPLETE_COURSE" definitions. The "Confidence" is very high since 49 of the 57 participants dropped out of the course, representing 86% of the successful cases of the rule.

As indicated above, to validate these rules, the results analysis was extended to obtain the pass rate of the rules in terms of "Passed" and "Failed" students. Thus, for the same rule 1, 51 participants "Failed" the course, representing 89.5% of cases in compliance with this rule based on the course's pass or fail criteria.

"ABANDONA" means DROPOUT

Figure 4 shows the result of the first 10 rules. As is logical, some questions belong to more than one rule, i.e., they are combined according to the type of answer. We also observe two and even three responses in certain rules that contribute to generating a new rule.

Rule 1, which registers the highest confidence level, is structured based on the responses to questions 11 and 14. Question 11 asked participants about "Previous experience with MOOCs." The five response options were "This is the first time I have enrolled in a MOOC," "I had already enrolled in at least one MOOC but did not finish it," and the other three alternatives indicated whether they had finished one, two, or three or more MOOCs. Of the options, the response chosen by the participants was the second one, indicating previous experience in a MOOC without finishing it. This option is interesting to analyze for two reasons: first, the motive to abandon a course again, such as the present energy subject, would not be due to the topic itself; second, there was already a predisposition and a history of abandonment.

On the other hand, Question 14 asks, "Which of the following options best describes your interest in enrolling in this course?" The response alternatives were: a) Out of curiosity; b) Because I want to have contact with other students interested in the subject; c) I have friends in the course; d) The course is related to my academic program; e) The course is related to my job; f) The skills will help you get a better job, and g) Other (specify). Here the alternative selected was "f," which refers to getting a better job. In this case, it is striking that, although they enroll in the course to get a better job, they do not complete it.

The rule in the second position of the confidence index contributed four questions. The first related to gender, which corresponded to females. The second concerned the educational level. In this question (number 8 in the survey), the options were high school, technical career, bachelor's, masters and doctorate. The option selected by the participants was a bachelor's degree. The third question (number 11 in the survey) was described in the previous paragraph, and the option chosen was "It is the first time I enrolled in a MOOC." The fourth question (number 24 in the survey) stated, "I think I have the necessary competencies to study this course through a technological platform." The response chosen was "Strongly Agree." (The other options were Agree, Disagree and Strongly Disagree.) Analyzing the four responses of rule 2, we observe that women with a bachelor's degree enrolling for the first time in a MOOC and having the technological competencies were the ones who dropped out of the course. Here, it could be concluded

Table 1: List of first ten rules generated with their respective data.

Rule	Antecedent	Consequent	Records that meet the conditions of the Antecedent	Compliance Cases	Support	Confidence	Failed	Failure rate
1	IC1.R11=='Ya me había inscrito en al menos . . .. ' & IC1.R14=='Las habilidades y conocimientos ...'	'ABANDONA'*	57	49	0.033	0.86	51	0.895
2	gender=='F' & level_of_education=='Licenciatura' & IC1.R11=='Es la primera vez que. . .. . .' & IC1.R24=='Muy de acuerdo'	'ABANDONA'	58	46	0.031	0.793	46	0.793
3	level_of_education=='Licenciatura' & IC1.R11=='Ya me había inscrito en al menos . . ..'	'ABANDONA'	66	51	0.034	0.773	54	0.818
4	IC1.R11=='Es la primera vez que me inscribo a un MOOC.' & IC1.R14=='Por curiosidad . . ....' & IC1.R21=='En desacuerdo'	'ABANDONA'	61	47	0.031	0.77	49	0.803
5	IC1.R11=='Ya me había inscrito en al menos . . ...' & IC1.R22=='Muy de acuerdo' & IC1.R25=='Muy de acuerdo'	'ABANDONA'	87	67	0.044	0.77	69	0.793
6	IC1.R12=='Si, pero no influyo en mi decisión de . . ..' & IC1.R14=='Las habilidades y conocimientos que . . .. ' & IC1.R21=='En desacuerdo'	'ABANDONA'	69	53	0.035	0.768	56	0.812
7	IC1.R12=='Si, pero no influyo en mi decisión de . . ....' & IC1.R21=='En desacuerdo' & IC1.R25=='Muy de acuerdo' & IC1.R26=='Muy de acuerdo'	'ABANDONA'	73	56	0.037	0.767	60	0.822
8	gender=='f' & level_of_education=='Licenciatura' & IC1.R12=='Si, pero no influyo en mi decisión de . . ...' & IC1.R24=='Muy de acuerdo'	'ABANDONA'	64	49	0.033	0.766	51	0.797
9	IC1.R11=='Ya me había inscrito en al menos un . . ..' & IC1.R19=='Muy de acuerdo' & IC1.R22=='Muy de acuerdo'	'ABANDONA'	66	50	0.033	0.758	53	0.803
10	IC1.R11=='Ya me había inscrito en al menos un . . ...' & IC1.R18=='Muy de acuerdo' & IC1.R22=='Muy de acuerdo'	'ABANDONA'	74	56	0.037	0.757	59	0.797

Table 2: Description of survey questions, rules and responses.

Question code	Rules	Question	Selected response alternative
IC1.R04	R2, R8	Gender	Female
IC1.R08	R3, R8	Education level	Bachelor's Degree
IC1.R11	R2, R4	Previous MOOC experience.	This is the first time I have enrolled in a MOOC.
	R1, R3, R9, R10		I had already enrolled in at least one MOOC but did not finish it.
IC1.R12	R6, R7, R8	Did you know Tecnologico de Monterrey before this course?	Yes, but it did not influence my decision to enroll in the course.
IC1.R14	R4	Which of the following best describes your interest in enrolling in this course?	Out of curiosity (to know what a MOOC consists of).
	R1, R6		The skills and knowledge provided by the course will help me get a better job.
IC1.R18	R10	I believe this course will be able to improve my job or business opportunities (current or future).	Strongly agree
IC1.R19	R9	I believe that this course will make it easier for me to establish professional relationships with people who have interests similar to mine.	Strongly agree
IC1.R21	R4, R6, R7	I believe I have the consistency to successfully complete this course.	NO. Strongly agree
IC1.R22	R5, R9, R10	I believe I have the skills (study skills, ICT skills, etc.) necessary to successfully complete this course.	Strongly agree
IC1.R24	R2, R8	I believe I have the necessary skills to study this course through a technological platform.	Strongly agree
IC1.R25	R5, R7	I believe I have the necessary skills to get relevant information on the topics of this course.	Strongly agree
IC1.R26	R7	I believe I have the necessary skills to use social networks for academic purposes.	Strongly agree

that taking a MOOC may not be what they expected. In the other responses, it was not possible to reach a significant association or level of analysis.

In Figure 4, the color intensity and circle size defined for each rule have meaning. For example, rule 5 is larger because many participants answered the questions that are part of the rule. The color indicates the confidence level of the rule. The more accentuated it is, the higher the level of confidence and precision found in the results. Table 2 details the rules generated and the answers chosen.

As can be seen, the responses led to the rule constructions. Some rules shared responses.

5 DISCUSSION

Attrition or dropout in MOOC courses is a research topic that can be analyzed through the KDD methodology, using association rules. Table 1 shows the results of the generation of rules demonstrating, through the participants' answers, particular behaviors related to dropping out of a MOOC course on energy sustainability. Although the KDD methodology is applied in other fields, in this context, its objective is to understand and digest more easily the voluminous data to discover and extract patterns [25]. Regarding the attrition problem in MOOCs, these figures are of interest to institutions and MOOC provider platforms and those researching the MOOC phenomenon. Actions must be proposed to increase retention [22]. The ultimate goal is to improve retention. Therefore, analyzing participants' responses and behavior with this methodology is a mechanism to understand MOOC dropouts, which would lead to proposing actions for improvement.

Evidently, a predominant factor underlying attrition in MOOCs is motivation, which needs to be analyzed. As Figure 4 shows, rule 1 was generated from the participants responding in the initial survey, "I had already enrolled in at least one MOOC, but I did not finish it" and "The skills and knowledge provided by the course will help me get a better job." From these responses, we concluded that those participants who answered both questions similarly became potential dropouts.

The aspiration to get a better job is an intrinsic motivation, which, together with other motivations, makes the participant enroll in a course [19]. In this sense, [17] agrees, pointing out that promotion at work or achieving a better position in their job is an essential factor. Based on our analysis, motivation is an issue that influences attrition, which is not new; however, if the participants were detected in this relationship as presented in rule 1 at the beginning of the course, actions could be established to improve retention and terminal efficiency.

6 CONCLUSION

This article shows that using association rules allows identifying with a high precision and confidence level the participants' behavior in the MOOC course on conventional and clean energy and its technology since the results obtained from 0.86 to 0.75 reflect a good level of "Confidence." This study provides evidence that a high percentage of the total population associated with each rule drop out of the course. Therefore, from the participant's responses on the initial survey, it was already possible to determine those who would potentially drop out of the course.

The methodology used allowed us to identify elements and reach significant conclusions. Also, we obtained results that make it possible to generate strategies to improve the results of future MOOC courses. The present study constitutes a knowledge base to establish the participants' behaviour through the answers they provided. We recommend that a broader study be carried out to observe the progress and development of the activities week by week and identify other elements not addressed in the present study.

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