EFFECTS OF BIAS, GAMIFICATION AND MONETARY COMPENSATION ON MOOC DROPOUTS

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ABSTRACT

The dropout rate is the most significant disadvantage in Massive Open Online Courses (MOOC); most of the time, it exceeds 90%. This research compares the effect of cognitive bias, gamification, monetary compensation, and student characteristics (gender, age, years of education, student geographical location, and interest in the course certificate) on dropout. We use survival analysis to identify the predictors of dropout and its related factors. The results showed the lowest dropout (74.2%) for cognitive bias and gamification. The results showed that the Peanut effect bias favors the lowest risk of drop up. Likewise, the findings showed the interest in the final certificate as a predictor of retention to complete a four-week MOOC.

Keywords: MOOC, gamification, choice bias, monetary compensation, Peanut Effect.

INTRODUCTION

Retention is one of the biggest challenges in Massive Open Online Course (MOOC), and it is expressed as Terminal Efficiency (TE) or percentage of students who complete a course. The terminal efficiency of MOOCs is between 9.5% and 10% (Montoya et al., 2022; Garcia-Leal et al., 2021; Goopio & Cheung, 2020) and is influenced by cultural contexts and social networks via the internet (Bozkurt & Akbulut, 2019). Retention has been approached from different models: Composite Persistence (Rovai, 2003), Revised CPM (Park, 2007), SIEME Model (Chyung, 2004), Model of Adamopoulus (2013), and finally the Model of Retention and Decision for Open Learning Environments (AMOES, Gutl et al., 2014) that groups the variables raised in the previous models. According to these models, TE can be associated with online gamification (setting experience), cognitive biases, monetary compensations and student characteristics.

This research presents the continuation of the analysis of dropout in a MOOC carried out by Medina-Labrador et al., (2019) by adding three factors: gamification, choice bias, and monetary compensation. The course analyzed was offered through Coursera in Spanish. This study considered the variables of gender, age, educational level of the students, and the continent of origin of the participants. The research questions considered were:

1. Is choice bias, presented as the number of questions at the time of the evaluation, associated with attrition in MOOCs?
2. Can gamification decrease dropout? What are the best predictors of dropout?
3. Does monetary compensation, granted as reinforcement and considered as a discount in the payment of the MOOC, reduce dropout?

In this study, we use survival and risk analysis to answer the questions presented; our main goal was to know the combined effect of choice biases (number of questions asked), monetary reinforcements, and games on survival and risk attrition.

Cognitive Biases

Traditional economics is a rational-choice paradigm that suggested decision errors can be interpreted as instances of misweighting (putting either too much weight or too little weight on specific types of costs and benefits); when this happens, the use of cognitive bias produces a compensatory reweighting that offsets the initial misweighting (Loewenstein et al., 2013). From the behavioral economics approach, people make decisions in two phases: edition and evaluation—first, the results are ordered under a heuristic scheme to establish a reference point. The highest results are classified as gains and the lowest as losses. Second, the evaluation assesses the utility and selects the one that has the most significant result with their respective probabilities (Kahneman & Tversky, 1981; Loewenstein et al., 2010; Thaler & Benartzi, 2004). However, most decisions are made intuitively through fast paths called cognitive biases (Kahneman, 2003). These biases are used to face complex or unknown tasks (Referencia), pressure situations (Furse, Punj & Stewart, 2016), and aversion to loss in small monetary amounts (Shimizu & Udagawa, 2018).

Cognitive biases have been used to nudge behavior in different areas such as health (Loewenstein et al., 2013; Kullgren et al., 2013) and finance (Thaler & Benartzi, 2004). For example, the "peanuts effect" bias states that people are more willing to gamble when playing for "peanuts" (a small outcome). It means, people do not care about the risk or consequences when gambling small amounts or efforts (minor behavioral changes), and as a result, they are willing to risk "small amounts" doing something that implies little-gradual-changes. To describe the effect of decreasing risk-aversion with decreasing monetary rewards (e.g., a student who spends little time answering a test with few questions will reassess the decision to follow or drop out of a MOOC based on the cost-benefit of their efforts). Likewise, the underestimation of delayed consequences is included within this bias, and it happens when people only see the current benefits without long-term consequences consideration (e.g., a student who passed an exam after answering a few questions will underestimate the gradual effect of the questions and the consequences in the future for not knowing all the content to be addressed).

Medina-Labrador et al. (2019) found that the peanuts bias effect favored TE when few evaluative questions were applied in week one, with low increases in the MOOCs, compared to the courses that used several fixed courses evaluative questions during the learning weeks. The peanuts effect bias has been used in settings other than learning. According to the National Federation of Consumers of the United States, 82% of citizens like the idea of saving; however, they feel unable to start because they believe they should do it with much money. Thaler & Benartzi (2004) research results show that employees felt more motivated when they allocated small amounts of money to start (3 USD) instead of more significant amounts. In the medical sector, the peanuts effect bias has been successful among weight request programs for overweight subjects. Studies by Loewestein et al. (2010) show that overweight patients undergoing a weight loss treatment in small daily pounds (0.16 lb.) were more likely to remain in the program than the group who were asked for high fixed amounts of weight (2 lb.) for two months.

Gamification

Gamification, seen as the consumption and use of games in non-traditional environments, can be used in internal factors, in students, in the factors of the MOOC provider, and in the expectations of the operation. Gamification is defined as a process and set of experiences in learning environments, based on the idea of solving problems, creative thinking and elaboration of decision strategies (Sezgin & Yuzer, 2022). Different authors interpret the concept of gamification based on the principles; goal orientation, reinforcement of knowledge, competition, skills and fun. Likewise, the literature reports different dimensions of gamification: logistics, interaction, comparison, psychological and economic gains. Gamification provides an experience that favors consumption by providing a motivational experience and purchases intention, looking for fun, excitement, and sensory estimates. Games have internal consequences for consumption since their experimentation is immediate and fulfills affective functions by acting positively (Sailer et al., 2013).

Setting experiences as gamification have shown to favor retention in the use of MOOCs (Gene et al., 2014; Romero-Rodriguez et al., 2019). The prizes in engaging activities (Collazos et al., 2016; Ortega-Arranz et al., 2019) and the learning tasks in games motivate students to stay and finish the course (Gupta & Vaibhav, 2014; Aparicio et al., 2019). Those games that use material goods online have the highest efficiency rates (9.52% TE), redeemable points (8.45% TE), and team leaderboards (7.34% TE) (Chang & Wei, 2015; Krause et al., 2015). According to An et al., (2021) the use of gamification in MOOCs increases students' social interactions by 91.6%, retention 85%, and level of learning (52.3%). This research reports other results: young people between 20-49 years old are more likely to use gamification, and students who had previous experience in gamification are more likely to use a game again in MOOC. However, gamification presents drawbacks among students: lack of time, inconsistency between the course content and the proposed game, and lack of funding to take the courses.

Based on De Notaris et al., (2021), gamification has also been combined with simulation for the learning of soft skills and business strategies, achieving a higher level of learning in the participants and a lower dropout rate. According to Rincon-Flores et al., (2020), gamification achieved a dropout rate of 12.89% in technologies and clean energies, establishing a positive relationship with participation during the course and motivation. The participants presented an interval of acceptance of gamification between 95.6% -97.3%, and this strategy helped them in their learning process during the course. The implementation of games increased the cognitive dimension among students between 21-30 years old; men accepted the games in the form of challenges to solve problems, while women did so with the leader board.

Monetary Compensation

From the perspective of behavioral psychology, the reinforcements used to improve retention in MOOCs may not necessarily be monetary, but they can be tangible, unlike physical money that can be perceived as compensation rather than a reward. 60% of employed students did not drop out since they considered this incentive durable (Sureephong et al., 2020). Monetary compensation favors decision-making. Loewenstein et al. (2010) proposed an activity to reduce fuel consumption and promote public transport. This activity was presented through a rewards system based on a raffle, motivating the participants through a monetary prize. Through an electronic ticket card, passengers who used the transportation system that day would be informed daily about the card winner (prize). People would be expected to increase their transportation system use because of the slim chance of winning a monetary prize. This approach shows monetary compensation in non-habitual contexts of consumption (Deterding et al., 2011).

METHOD

This research used a quantitative methodology with a longitudinal non-experimental study, and the information was collected in 2020. A university offered the MOOC, and the participants were recruited by social network in Colombia. The cost of the final certificate was 49 USD. The course belonged to the discipline of engineering, in the area of sales forecasts for beginner salespeople. The MOOC was carried out over four weeks, during which the participants had access to written information, interaction with the teacher to solve questions, and games at the time of the evaluations. The learning contents were supplied week by week and at the end of each week the participants received the evaluation and compensation according to the case. Two types of studies were applied: (a) experimental type, with "pure" experiments with two or more comparison groups. (b) non-experimental longitudinal trend design type.

Participants

Participants were 1,289 students from mainly Spanish-speaking countries registered in a popular online educational platform. The characteristics of the study population were predominantly male (64.4%) and 34 years old on average (SD = 9.5) distributed in the ranges 18-28 (32.1%), 28-38 (39.7%), 38-48 (17.3 %), 48-58 (6.9%), 58-68 (1.5%) and > 68 (2.5%), The mean level of education (according to the USA Educational System) was 16.7 with a standard deviation of SD = 2.6. Student were from South America (68%), Central America (21.7%), Europe (7.3%), North America (1.7) Asia (0.6%), Africa (0.6%). The students were recruited through digital advertising for two months, and the course lasted for four weeks. Participants who took the course at their own pace, those under 18 years of age, 80 individuals who did not sign the informed consent, and those who had previous experience with MOOCs were excluded from participating in the research. There was only one start date; after this date, the course was closed for any enrollment.

Data Collection

Information was gathered from a university platform through three different data set: (1) Registration, (2) interest in the Certificate, and (3) Weekly evaluation. The weekly evaluations were carried out based on previous investigations of Medina-Labrador et al., (2019). The weekly evaluation test was multiple-choice questions, and the response time was one day. Therefore, it was not possible to return to correct the answer. After the evaluation was finished, the individuals continued with the next module. Participants received the informed consent forms and signed them before starting the experiment.

The MOOC took as its primary theme the forecasts of commercial demand. The cost of the certificate was 49 USD. The duration of the course was four weeks.

Three types of studies were applied: (A) Experimental type with two or more comparison groups "pure" experiments. (B) Survival analysis and (C) Longitudinal non-experimental type of trend design type. The participants were randomly assigned to each factorial group, depending on the experimental factors (peanut bias, game, and monetary compensations); absence or presence of factors, and the homogeneity of the participants in the factorial groups was guaranteed (Table 1). The results were analyzed according to the three established phases. All stages used SPSS version 27.

Table 1. Experimental design and number of individuals per experimental group

	Without Peanut Effect Bias		With Peanut Effect Bias	
	With $1	Without $	With $1	Without $
With game	168	183	154	178
Without game	178	166	176	86

In Phase 1, a descriptive and relational analysis was performed based on attrition. In Phase 2, a 2x2x2 factorial design was carried out; Students' dropout behavior was analyzed in two groups (peanut effect): (1) Number of weekly variable questions (5, 7, 9, 11) and (2) Number of fixed questions weekly. (8, 8, 8, 8). Subsequently, each group was subjected to two factors: gamification and compensatory consideration. The levels of both factors were absence and presence. For gamification, a digital roulette was used where the student who finished a week could receive 1 USD or 0 USD as a discount to purchase the final certificate. In the case of the compensatory consideration, the participants could receive 1 USD for each week finalized and take that money as a discount in the final certificate. The students were randomly assigned to each experimental group (Table 1). The design presented a small magnitude $\omega 2 = 0.1$ and a power of 0.7.

Data Analysis

The analysis was carried out based on the steps contemplated and the experimental part through two-way factorial analysis; where the positive effect of the minutiae bias and gamification on droop out was found. Survival Analysis curves in MOOCs have shown that desertion decreased 80% during the first week, and the probability of dropout is affected by: the peanut bias represented in the numbers of questions, the education level, the age level, and the interest in the certificate. From a predictive point of view, the Cox Regression showed that interest in the certificate is a predictor of dropout (Medina-Labrador et al., 2020). Yang et al., (2015) found that the probability of desertion is low when there are collective experiences in synchronous reflection exercises, and the risks of desertion increase with the number of attempts to correctly solve the exam questions. The risk of dropping out increases when there is disinterest in the certificate and lack of commitment during the course. The details of the analysis by steps can be seen below.

FINDINGS

In the first descriptive and relational phase, the total dropout rate in this MOOC was 92.9%. The results allowed us to identify that the highest terminal efficiency is found in the group with peanut effect bias, gamification, and without monetary compensatory (25.8%); that is, desertion of 74.2%. The group with the lowest terminal efficiency was that without "Peanut effect" bias, without compensatory consideration, and without gamification (1.2%); in conclusion, a dropout rate of 98.8%. Statistically significant differences were found between attrition and the experimental groups $\chi 2$ (7, N = 1,289) = 100.33, $p <.0$ and also between attrition and "peanut effect" bias $\chi 2$ (1, N = 1,289) = 25.86, $p < .0$. Students belonging to the group of fixed amounts (no peanut effect bias) had a 33.2% higher risk of attrition (OR = 0.33) than those of the variable question amounts (95% CI between 0.21 and 0, 51). No associations were found between dropout and gender, age, educational level, and continent.

In the second experimental phase, the inter-subject tests show that the model is significant $\chi 2$ (7, N = 1.289) = 92.96, $p <.0$. Significant effects were found with the week of attrition and the factors: peanut bias $\chi 2$ (1, N = 1.289) = 26.08, $p <.0$, peanut bias and gamification $\chi 2$ (1, N = 1.289) = 6.37, $p < .0$, "peanut effect bias and compensatory reinforcement $\chi 2$ (1, N = 1.289) = 33.76, $p <.0$ and compensatory reinforcement and gamification $\chi 2$ (1, N = 1.289) = 22.31, $p <.0$. The highest partial squared Eta value was presented in the peanut effect segment (EPC = 0.16) and the lowest in gamification and peanut effect bias (EPC = 0.04). There were no effects of the factors gamification, compensatory remuneration, and the combination of gamification, compensatory remuneration, and peanut bias. Regarding the experimental groups, significant differences were found for the drop-out week f (7, N = 1.289) = 10.55 $p <.0$. Tukey's test indicated that there are two homogeneous subsets; the group with the greatest permanence in the course is the one that contains gamification (M = 1.12); the other groups reported a mean (0.21 - 0.55).

In phase 3, the survival and risk analysis were performed for each type of bias; the influence of the study variables on survival was then analyzed through the operator of Kaplan-Meier, and finally, a Cox regression was carried out to know the influence of the associated variables in the last dropout. In the results of Phase (3) of the survival analysis, the probability density function was estimated for each factorial design. Dropout and dropout probability were analyzed weekly; initially, the study was carried out without the influence of covariables and later with the independent variables associated with attrition. The results indicate that the probability of survival is higher in the group of variable questions (with bias) (24%) compared to the group of fixed questions (without bias) (17%) during the first week. At the end of the fourth week, the probability of survival is higher in the variable quantity group (12%) than for the fixed group (4%). Likewise, the cumulative dropout risk index is higher in the group with fixed questions during the first week (IR = 69%) than that of the group with variable questions (IR = 34%) (Figure 1).

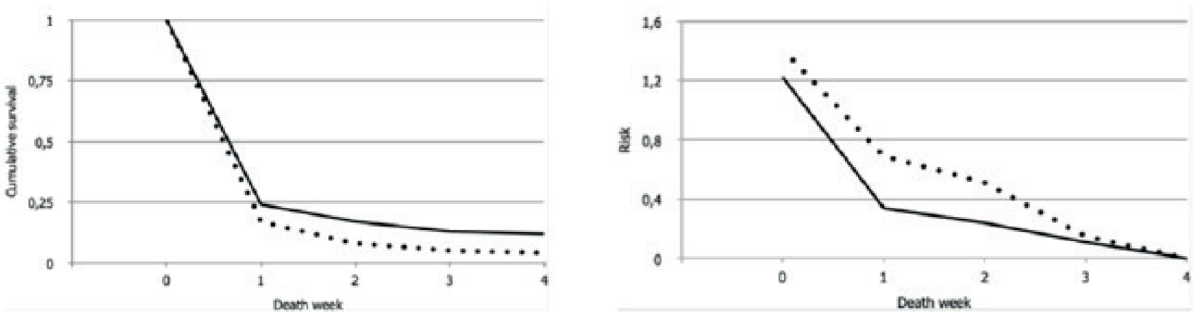

Figure 1. (a) Left. Probability of survival as a function of bias. (b) Right. Cumulative risk probability as a function of bias. (.) Without bias. (-) With bias.

Regarding survival and risk within the experimental groups, the best survival function and median week of death (0.74) is group three with gamification and “Peanut effect” bias. Group five, without compensatory reinforcement, without gamification, and without “Peanut effect” bias, had the lowest median week of death (0.58). Regarding the risk of attrition, group five presents the highest function with a weekly risk of 1.48 in the first week, 1.23 in the second, 0.67 in the third and 0.40 in the last. Group three shows the lowest risk of attrition with a weekly risk of 1.02 in the first, 0.15 in the second, 0.08 for the third, and 0 in the last week (see Figure 2).

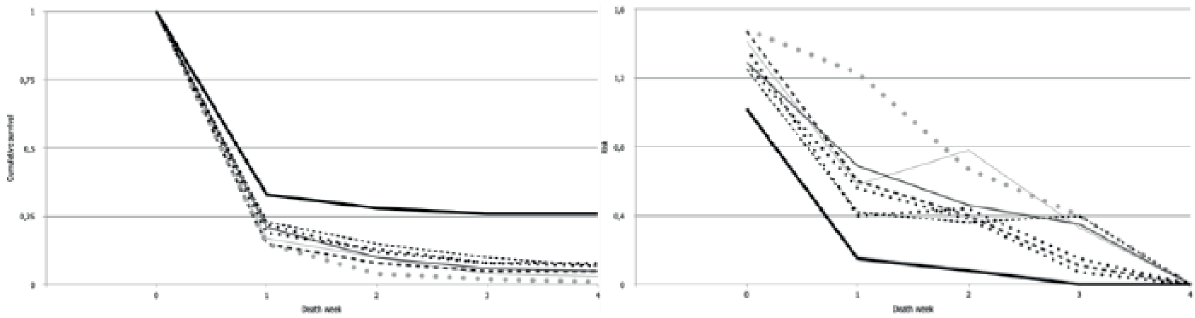

Figure 2. (a) Left. Cumulative survival function with 95% confidence interval. (b) Right. Risk function.

Within this same Phase 2, dropout was analyzed by a multiplicity of probabilities independently for each student and the probability of dropping out in a given week. The survival functions were calculated through the Kaplan-Meier estimator during the maximum period of weeks.

Statistical differences between the survival function and the covariates were made through the Log-Rank test. No influences of gender, continent, education, and age were found in the probability of dropping out of the MOOC participants over time. The results indicated that the increased probability of MOOC attrition is due to: “Peanut effect” bias $\chi2$ (1, N = 1.289) = 24.71, p <.01, compensatory reinforcement $\chi2$ (1, N = 1.289) = 5.43, p = 0.02, gamification $\chi2$ (1, N = 1,289) = 5.10, p = 0.01 and interest in the certificate $\chi2$ (1, N = 1,289) = 123.62, p <.01.

The predictors of risk of attrition and the influence of the covariables on attrition in each bias were analyzed based on a Cox Risk Regression model. The covariables included were gender, age, gamification, monetary compensations, interest in the certificate, and type of certificate. Attrition was estimated as a state variable, and the duration of the MOOC in the four weeks was the moderating variable. 1,289 cases were available for analysis, with 75 censored data. The model frame was estimated based on the forward progressive regression method and the likelihood ratio. The model was adjusted in the first step, showing no changes from step N-1 to N 1. The omnibus test indicates in the fourth step that some of the selected variables contribute significantly to the model χ^2 (1, N = 1.289) = 87.27, p <.01. The variable interest in the certificate was estimated as in the equation as the variable that presented the highest predictive value for risk of desertion

χ^2Wald (1, N = 1.289) = 20.16, p <.01. The weighted average Hazard ratio shows that globally the dropout rate is 23.4 times higher if the students are not interested in the certificate Exp (B) = 0.23. The other variables are not present in the equation.

DISCUSSIONS AND CONCLUSION

High dropout rates are one of the biggest problems in MOOC development. In this study, attrition was analyzed through a single topic MOOC with a 2x2x2 factorial experiment, with the factors: “Peanut effect” bias, gamification, and monetary compensations. The findings of this research expand the Online Learning Participation Tunnel factor and the level of activities proposed by AMOES since it found the lowest dropout rate (74.2%) in the group of participants subjected to the bias of the “peanut effect ”(Variable of questions and participants in the proposed game). Furthermore, the attrition rate achieved improves the range reported in the literature (Carey, 2012; Chang & Wei, 2016; Goopio & Cheung, 2020; Gutl, Chang et al., 2014). In addition, these findings show the importance of including variables related to purchasing intention (interest in the certificate, participation in games, compensatory considerations, and choice biases).

The inferential findings associated with attrition are also consistent with those reported in other research: gamification (Chang & Wei, 2016), “Peanut effect” bias, and compensatory considerations (Loewenstein et al., 2000). This study succeeded in (a) adapting student concepts in consumption from the offline world to the digital realm (“Peanut effect”) and (b) measuring behaviors of a user of new technologies such as a MOOC, through basic psychological procedures such as motivation and cognitive processes such as effort. This study provides a predictive model of dropout behavior in MOOCs related to the efforts and expectations of students.

Offline research demonstrated the influence of choice biases on individuals’ decision-making. It found that the number of variable questions (5, 7, 9, 11) and the use of games such as roulette increased survival in the last week from 24% to 40%. Similarly, the influence of these factors increases the probability of survival from the first week to the last and decreases the risk of desertion reported by Medina-Labrador, 2019. Additionally, the results showed that if there are few questions at the beginning and many at the end and the roulette game is added as motivation to watch the videos, desertion decreases.

The findings of the survival analysis are consistent with the results of Medina-Labrador et al., 2020 regarding the risks of dropping out during the first week of the course. A critical aspect was the predictive capacity of dropout of the “Peanut effect” bias variable reflected by the fact that variable amounts of evaluative questions decrease dropout. The Cox regression analysis confirms what was found by the binary logistic regression regarding the presence of the “Peanut effect” bias and gamification bias. Likewise, the effect of gamification and performance expectations are consistent with reports in the literature (Chang & Wei, 2016; Venkatesh et al., 2003). This research showed that the undervaluation of the efforts required to finish a MOOC is 9.3 times lower when few questions are presented initially and increase each week. Similarly, students subjected to fixed evaluation questions dropout 33% more than those who have incremental variable amounts. Likewise, the “Peanut effect” bias coupled with gamification achieves a terminal efficiency of 25.8%. These results support those found in the offline world by Loewenstein et al., (2000) to help consumers make responsible decisions for themselves.

This research suggests the development of pedagogical strategies aimed at reducing dropouts during the consumption of MOOCs by analyzing their operation, the efforts of the students, and the conditions of ease of use. The results specifically suggest that dropping out of MOOCs is due to a lack of interest in the certificate, low participation in the proposed games, and apathy to present efforts. These outcomes are consistent with recent reports from the literature and bring the results to an inferential level. On the other hand, and taking into account that the students were Colombian, the internal geographic origin within the country may affect each of the manipulated factors, taking into account their meaning, something that is consistent with Bozkurt & Akbulut (2019).

Low number of questions at the beginning increased the cumulative survival during week two, from 51% to 62%, and decreased the cumulative risk of attrition during the same period from 12% to 4%, respectively. The “Peanut effect” bias works not only as a strategy to increase the survival rate and decrease risk, but also operates as a motivator in the intention to consume MOOCs and explains the expectation of effort, decreasing cognitive effort. This effect extends the studies on survival and risk in MOOCs (Medina-Labrador et al., 2022; Ferschke et al., 2015; Yang et al., 2015), highlighting survival’s association with participation in forums, videos, and joint activities that entertain the student. This research provides significant evidence to intervene in the first week of the courses, specifying the results reported in the literature (Greene et al., 2015), and explaining the final dropout rate of 74.2%.

Finally, the effect of gamification on the attrition behavior and experience within the MOOC turned out to have a high predictive value of attrition ($\beta = 3.4$). The results showed that gamification could foster the motivation responsible for initiating and continuing the behaviors aimed at completing the course. Perspectives of interest in the certificate, students' dropout trait, self-determination in the week of death, and emotion were evaluated. The monetary discounts linked to the game could act as immediate positive reinforcements since they are perceived as rewards for actions carried out (Sailer et al., 2013).

The survival analysis in education has been used to predict inertia and its associated determinants. The results show the predictors of dropout and its related factors (Stoolmiller, 2016). Survival analysis determines the probability that a subject is present during a time (life) segment until a moment of death (desertion). Likewise, it allows us to know the average time the individual stays within the study and its factors (Ferschke, Yang, Tomar & Rose, 2015; Greene, Oswald & Pomerantz, 2015). Survival analyzes used in MOOCs show that gender is a predictor of dropout; women have a 65.5% chance of dropping out compared to men. This behavior is only described during the first two weeks of the course. Other student characteristic variables, such as having an outgoing personality and previous experience in video games, decrease the probability of survival (Chen et al., 2020). According to Xie (2019), the duration of the MOOC videos and their area of knowledge lead to different probabilities of survival.

Looking holistically at the research, the results of the interventions, highlighted by related and experimental evidence, suggest the possibility of implementing a new expectation of effort using the "Peanut effect" bias, the implementation of gamification activities during the course, and the promotion of the interaction, to increase the intention of the consumption of MOOCs. Furthermore, the solutions presented contribute to redesigning digital tools to monitor the behavior carried out by a MOOC user to enhance acceptance of a new learning technology that is increasingly adhered to in the people's culture and daily lives.

The findings of this study are limited by the fact that the students took only one course on a specific topic related to mathematics. However, the results of this research are consistent with the findings of Medina-Labrador et al., 2019 in that there is a lower probability of dropout when the courses last four weeks and higher when it comes to study material related to mathematics. A change of subject might lead to different behaviors both in the enrollment motivation and in the permanence during the course. Based on the findings of this study, a longer duration of the MOOC may affect the attrition rate found. Future research should analyze other topics with different difficulty and duration levels. Likewise, it is advisable to identify the influence of the number or distribution of questions on choice biases.

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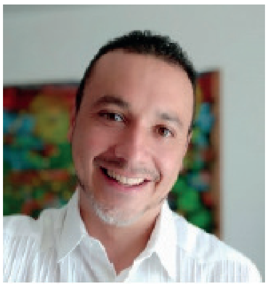

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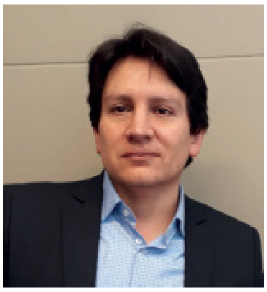

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