

# An Intelligent Adaptive cMOOC “IACM” for Improving Learner’s Engagement

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**Abstract**—Despite the massive number of enrollments in MOOC (Massive Open Online Course) platforms, dropout rates are very high. This problem can be due to several factors: Social, pedagogical, prior knowledge as well as a demotivation. To deal with this type of problems, we have designed an adaptive cMOOC (Connectivist MOOC) platform for each registered learner’s profile.

From the first human-machine interaction, the process adapts the learner’s need according to a pre-established model. It is based on the processing of statistical data collected by correspondence analysis and regression algorithms. Each generated learner’s profile will provide an adaptive navigation and pedagogical activities. The intelligent system presented in this work will be able to classify learners according to their preferences and learning styles.

**Keywords**—MOOC, cMOOC, adaptive learning, intelligent system, machine learning, correspondence analysis

## 1 Introduction

Learning is getting easier with digital resources deployed on the web [1]. Among these accessible resources we find MOOCs (Massive Online Open Courses) [2]. By MOOC developing, universities have facilitated and accelerated access to high-level learning, free or at a very low cost. However, the dropout rates of these are flagrant. According to J. Daniel, the completion rate does not exceed 7% [3]. This rate is approved by the Software Engineering course offered by the University of California Berkeley on the Coursera platform; for more than 50 000 subscribers, only 7% of them were able to complete their courses [4-5].

This dropout rate [6] can have several origins: demographic (sex, age, level of education, location, etc.), pedagogical [7], social [8], prior knowledge [9] on the subject of MOOC and the motivation [10-11] to pursue a MOOC [12]. The last factor has a great importance as designers try to develop more advanced tools to attract learners [13]. All these works try to understand the learners’ willingness and thus attach them to the course [14-15]. Historically, since its creation in 1989 by Tim Burners-Lee

[16], the web has gone from a Web 1.0 of documents in simple reading towards a Web 3.0 [17]. The latest, which is more intelligent, is based on an integrated Web experience, where the machine will be able to understand and classify data [18] as much as the Web is directed towards an artificial intelligence. This development will have a significant impact on online learning through the MOOC.

Indeed, since the invention of the term MOOC, by D. Cormier from Prince Edward Island University [19], it had followed this development, and their expansion has grown exponentially. Recently, some providers or adopters of MOOCs are trying to go towards Connectivist MOOCs (cMOOCs) [20-21]. The idea of this type of MOOCs aims at providing tools, facilitating interaction between learners and between learners and their instructors (learning connection building), towards social networks, discussion forums, mutual evaluation, direct virtual conferences (at the end of each course unit, or sometimes a full question and answer session once a month or every two weeks), etc. This puts the learner in a socially pleasant learning situation. The course is considered to be the fruit of collaboration [22] between the instructor and the learners. In the case of a cMOOC, the focus is more on the links between the learners and between the learners and the instructor than on the content [23].

This type of MOOC is revolutionary compared to previously existing MOOCs which were often of the transmissive type (xMOOC) [24-25]. The use of these creates the same pedagogical problems of a classical teaching: Filming courses exposed in the same classical way to put the learners in front of the same constraints and pedagogical challenges. Each targeted learner must follow the didactics and pedagogies imposed by the teacher, with limited interaction during the presentation of the course, without any adaptation to his skills, neither taking into account, his preferences nor his technical, scientific and social needs. This negatively affects his engagement [26] and performance [27]. Despite the massive number of registrants for a course, the number of active participants who follow the course from the beginning to the end is still modest in comparison to the first registered ones [12-28]. These xMOOCs occasionally proposes heavy questionnaires for users in order to improve the course proposals. The weakness of these questionnaires requires that providers leave them to the users choices. They are only presented after a certain time of access to these MOOCs, which is sometimes late for the learner.

In this work, we propose a platform model which allows providing adaptive cMOOCs to each learner’s profile for his first registration to the courses. Parallel to the evolution of the content on the platform [29], learners’ needs become more specific to their preferences. The main objective of this paper is to create an intelligent platform model that learns from users and adapts to them. For that, we will built optimizing starting fields from recording user’s data on the platform (future static data) and the machine will automatically simulate, from the first connection, the courses adapted to each enrolled learner according to the pre-established model. Once the learner starts using the platform, his profile will be updated as his activities progress, considering the socioconstructivist pedagogical approach [30], as well as the experiential model of Kolb [31] and the Dunn & Dunn model [32] to detect preferences and learning styles [33]. Authors aim at giving each user his needs at the right time. The

results of this paper are based on a survey administered to students from the Abdelmalek Essaâdi University of Tetuan (AEU) in Morocco [34].

## **2 Research Method**

### **2.1 Research method**

To reach the main objective, we shall respond to the following research questions:

RQ1: What are the minimum inputs to request from AEU students, to build an adaptive cMOOC to their needs?

RQ2: How do the selected factors influence the interest in collaborative learning among AEU students?

RQ3: How will the machine learn to provide an adaptive navigation, taking into account each learner’s needs?

The answers to these questions will allow us to build an adaptive model to each profile. So, we can offer attractive MOOCs to the learners according to their profiles. Indeed, the RQ1 aims at optimizing the minimal inputs that will affect the learning process via an adaptive platform of cMOOCs. The RQ2 aims at determining the factors which influence more the interest in collaborative learning among AEU students. These parameters will constitute the initial inputs that the learner must enter when registering for the first time, while the RQ3 aims at explaining the architecture and the interactions between the different layers and factors of the adaptive system during the learning process via the platform.

### **2.2 Empirical study**

In order to know the profile of preferences related to the socio-constructivist learning of our students, we were interested in the answer to a survey, dealing with the problem raised. It was administered to a representative sample of 383 of the students. We used the stratified random sampling method which gives a better representation in our case. The 13 establishments coming from the AEU are considered as strata, the draw was done from each of these strata, and we considered a second level of strata which is the diversity of the fields of study.

In order to ensure that the heterogeneous students (Arabic-speaking and French-speaking) understand the survey; we have established Arabic and French versions validated by a white test group. In this work, we are interested in the social factors inducing the acceptance of MOOCs as being essential factors for learning or a complement to other soft skills. These factors are: Sex, age category, professional situation, establishment of the AEU, the diploma obtained, the field of study, comfort with technology and prior knowledge about MOOCs. In order to achieve the objective of our study, we used Correspondence Analysis (CA) algorithms to minimize the factors influencing learning through an adaptive cMOOC.

### 2.3 Factor analysis and linear regression

The CA allowed us to analyse the existing link between the qualitative variables and to reduce the factors to have those which maximize the explanation of all the variables. We opted for this data analysis method in order to optimize the number of input parameters that will affect the learning process via an adaptive platform of cMOOCs based on the socio-constructivist approach. A linear regression equation will be presented linking the input variables (the socio-constructivist factors  $X_n$ : sex, age category, professional situation, establishment of the AEU, diploma obtained, field of study, comfort with technology and prior knowledge about MOOCs) and the output variable (interest in MOOC learning based on the socioconstructivist approach  $Y_i$ ).

$Y_i$  is the interest in MOOC learning output understood by 3 variables:

Y1: Interest in collaborative learning

Y2: Interest in contributing to the design or the construction of the course

Y3: Having social media accounts for learning reasons

And the linear regression equation is:

$$Y_i = \sum_{n=1:3} a_n X_n \quad n \text{ from 1 to 8 (before Analysis)}$$

This paper considers only the results concerning Y1. The selection criteria of the main factors will be based on Cronbach's alpha as a reliability index, which must be greater than 0.65 minimum acceptance threshold [35], and the percentage of the explained variance for the eigen values greater than 1 [36-37].

## 3 Results

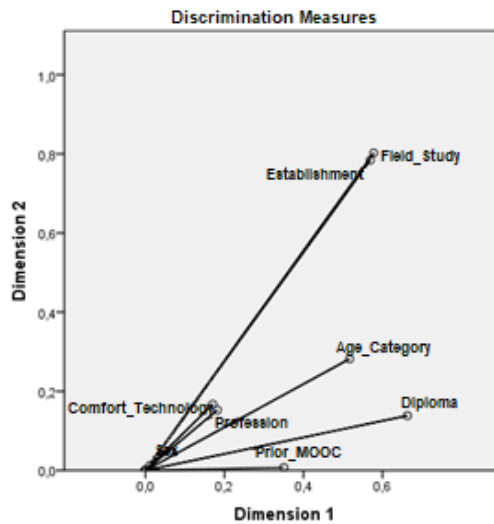
### 3.1 Reduction of factors

By using SPSS software, two dimensions have been chosen which provide a good deal of information. These dimensions verify the conditions given (Cronbach's alpha is good for dimension 1 (0.767), and acceptable for dimension 2 (0.656). The eigen values are 3.04 and 2.35 respectively and the percentage of explained variance is around 38% for dimension 1 and 29% for dimension 2.

**Phase 1:** In order to reduce the factors, we based ourselves on the discrimination measure crossing the two dimensions with the explanatory variables. This measure allows to know the factors least influencing the explained result which can be removed without losing the total information (See Table 1 and Figure 1).

**Table 1.** Discrimination Measures: Phase 1

	Dimension		Average
	1	2	
Sex	0.011	0.013	0.012
Age_Category	0.517	0.282	0.399
Profession	0.182	0.153	0.167
Establishment	0.569	0.784	0.677
Diploma	0.663	0.138	0.401
Field_Study	0.578	0.802	0.69
Comfort_Technology	0.17	0.167	0.169
Prior_Knowledge_MOOC	0.35	0.008	0.179
Total	3.04	2.347	2.694
Percentage of explained variance	38.005	29.334	33.669



**Fig. 1.** Inputs Reduce -Phase 1

The component matrix (see Table 1) indicates that the items: Sex, Profession, Comfort with Technology and prior knowledge about MOOC have little influence on the two factors retained.

**Phase 2:** In order to reduce the factors, we used the discrimination measure crossing the two dimensions with the explanatory variables. The reduction of these factors (by eliminating the factors whose measure is weak) and the review of the study gave the following results:

The Cronbach's alpha has been considerably improved, it has become very good for dimension 1 (0.820), and good for dimension 2 (0.720). In addition, the eigen values became respectively 2.599 and 2.175 and the percentage of explained variance went from 38% to 65% for dimension 1 and from 29% to 54% for dimension 2. Dis-

criminate analysis on the factors used shows a clear improvement in the correlations between these and variables.

**Table 2.** Discrimination Measures –Phase 2–

	Dimension		Average
	1	2	
Age_Category	.570	.177	.374
Etablissement	.685	.778	.732
Diploma	.648	.390	.519
Field_Study	.696	.831	.763
Total	2.599	2.175	2.387
Percentage of explained variance	64.986	54.379	59.682

In this second phase (see Table 2), these four selected factors have an improved explanatory influence: Category of Age, Establishment of the AEU, Obtained Diploma and Field of Studies, this is explained by the improvement of the average variance which went from 33% to 59%.

Once, the reduction of the factors is established, we will proceed to determinate an explanatory regression analysis based on the ANOVA method [38-39], in order to establish the conceptual model of the learners’ needs based on the socio-constructivist approach.

### 3.2 Analysis of preferences based on collaborative learning

The ANOVA method allows us to know if the dependent variable (variable to be explained) will be influenced by the independent ones (the factors retained).

Linear regression will reduce the differences in a sum of squares between a dependent variable and a combination of independent variables (the predictors). The estimated coefficients indicate the mode of allocation of the response due to changes in the predictors [40].

Table 3 Includes R2 and adjusted R2 which takes into account the optimal coding:

**Table 3.** Multiple R

Multiple R <sup>2</sup>	R <sup>2</sup>	Adjusted R <sup>2</sup>	Apparent Forecast Error
.318	.101	.082	.899

Although the coefficient is R2 equal to 0.101 which means dispersion around the regression line (10% of the variation of Y is explained by the variation of X), the absolute value of its square root is 0.318 which allows us to consider some linear correlation of the model. The following table (see Table 4) represents the results obtained from the first test of linear regression based on ANOVA. It includes the sums of the regression squares and the residuals, the average of the squares and the degree of freedom:

**Table 4.** Linear Regression Test based on ANOVA

	Sums of regression squares	Ddl	Squares Average	D	Sig.
Regression	38.729	8	4.841	5.259	.000
Residuals	344.271	374	.921		
Total	383.000	382			

This analysis was carried out in order to test the existence and the influence degree of the factors retained on the first variable explained  $Y_1 =$  Interest in collaborative learning.

Considering the null hypothesis and alternative as:

$H_0$ : All the factors of  $X_i$  are equal to zero.

$H_1$ : At least one of the coefficients is different from 0.

From the results in Table 5, it can be seen that the value of D obtained is greater than or equal to FTheoretical for the thresholds 1% and 5%, therefore the null hypothesis is rejected. This means that we have less than 1% to be wrong, affirming that the models obtained contribute to predict interest in collaborative learning.

**Table 5.** Coefficients Table

	Standardized Coefficients		ddl	D	Sig.
	Beta	Bootstrap (1000) Estimated standard error			
Age_Category	-.102	.107	2	.906	.405
Etablissement	.238	.068	2	12.450	.000
Diploma	.140	.091	2	2.357	.096
Field_Study	.158	.100	2	2.528	.081

The regression equation to predict a value of  $Y_1$  from the dependency variables  $X_n$  (with  $n = 1: 4$ ) at the threshold 99% is given by:

$$Y_1 = -0.102 X_1 + 0.238 X_2 + 0.140 X_3 + 0.158 X_4 + \epsilon_i$$

Table 6 shows the simple and partial correlations with Pratt's measures of relative importance for transformed predictors, as well as the tolerance before and after transformation:

**Table 6.** Correlations and tolerance

	Correlations			Importance	Tolerance	
	Zero Order	Partial	Part		Before transformation	After transformation
Age_Category	-.066	-.106	-.101	.066	.981	.994
Etablissement	.225	.243	.238	.531	.993	.989
Diploma	.121	.146	.139	.168	.991	.986
Field_Study	.151	.163	.157	.236	.985	.973

This Table 6 also presents the value and partial correlations. This is the way to gradually choose the predictor variables. The choice of the variables is however based on the importance of the strongest correlation between the variables which are always

available, and the part of variance which remains to be explained once we have removed it, which is explained by the first predictor.

## 4 Discussion

This section discusses the results found in this study, answering the various research questions already cited in the methodology section.

### 4.1 RQ1: Which are the minimum inputs to request from AEU students, to build an adaptive cMOOC to their needs?

To answer the question RQ1, we started by targeting the population studied through a survey, where eight parameters were considered in this initial stage: Sex, Age category, professional situation, establishment of the AEU, diploma obtained, field of study, comfort with technology and previous knowledge about MOOC. After doing a blank test, we had distributed the questionnaires and then collected the data. By treating this, we execute factor analysis algorithms in two phases. Finally, the results showed that among the eight input parameters, four were adopted for a significant explanation of the interest of students in collaborative learning [41]: Age category, establishment of the AEU, diploma obtained and field of study.

### 4.2 RQ2: How do the selected factors influence the interest in collaborative learning among AEU students?

To answer this question, a linear regression analysis based on the ANOVA method was applied in order to seek the influence degree of the factors retained on the interest of AEU students in collaborative learning. The results showed a significant model, where we could give the following regression equation:  $Y1 = -0.102 X1 + 0.238 X2 + 0.140 X3 + 0.158X4 + \epsilon_i$ .

Followed by correlation and tolerance tests, the results showed that three input variables between the four reduced marked a positive influence on the interest in collaborative learning among AEU students: The field of studies, the diploma obtained and the establishment. So, with regard to the first output Y1, these factors will constitute the initial part of static variables that the learner must enter during his first registration.

RQ3: How will the machine learn to provide an adaptive navigation, taking into account each learner’s needs?

In the literature, several studies discuss the possibilities of integrating learning styles in MOOC platforms [42-43-44], in order to personalize learning contexts and provide adaptive navigation. However, just thinking about learning styles is not enough to solve the problems that MOOCs platforms face, especially the high dropout rate [45]. Pedagogically speaking, the model of the adaptive system proposed in our work is based on the socio-constructivist model, the model of learning styles of Dunn & Dunn and the experiential model of Kolb [43-46]. Technically speaking, it is based



on methods of correspondence analysis, linear regression and classification algorithms of students across a neural network [44-47].

The auto updating system will provide an adaptive navigation, based at the beginning, on static data concerning the learner’s profile (up to now at the level of the results concerning Y1: The field of study, the diploma obtained and the establishment), evolving with dynamic data including pedagogical activities, learning styles and preferences, learning objectives, use and interaction in social environments, etc. [48]. Dynamic data will always be updated automatically, detecting the learner’s behaviour [49], activities and performance in his adaptive learning [50-51] environment. The architecture of our IACM approach with its various elementary components is described in the following Figure 2:

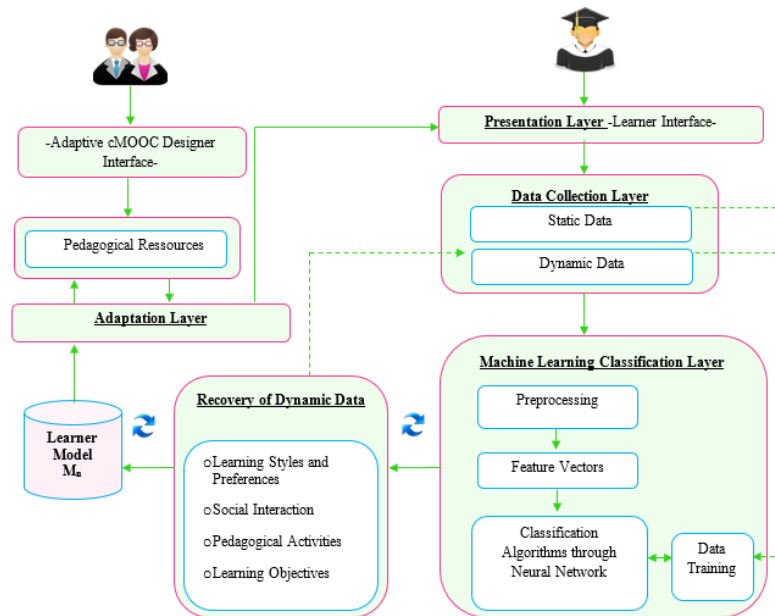


Fig. 2. Overview of the intelligent adaptive system

It includes six layers: a presentation layer (user interface), a data collection layer, a classification layer through a neural network algorithm, recovery of dynamic data and learner’s model building and an adaptation layer. After being registered in the platform and filling all the necessary input data, an initial learner profile  $M_0$  will be build.

Concerning the classification layer, the system will start with the preprocessing of the collected data, in order to keep the right information for the application of the neural network algorithm. Then the system will extract the characteristics which mostly reflect the learning styles and preferences, learning objectives, and degree of social interaction. On the basis of this data, the system will create vectors for each learner’s model in this step. These vectors represent the input of our model which will be automatically updated to the current learner’s model. This is very important for the

adaptation process, where each learner’s profile will be provided by navigation, resources and pedagogical activities adaptive to itself. Also, from this phase, the intelligent system will identify the classes of learners who demand the same preferences, styles and learning objectives to create groups of learners who share the same characteristics (see Figure 2).

## 5 Conclusion

The data analysed through this research work were collected from an empirical study, where a survey was carried out within the different establishments of the AEU (Tetuan-Morocco). After considering eight input parameters in a first step, the execution of CA method showed that the eight parameters could be reduced to four. Among these, three factors had positive impact on our first considered output, which is the interest in collaborative learning. These parameters will constitute the static variables provided by the learner during his first interaction with the intelligent system. The results obtained made it possible to propose a first intelligent model of these cMOOC platform, adaptive to the needs of AEU students based on classification algorithms through a neural network.

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