Hybrid Filtering Recommendation System in an Educational Context:
Experiment in Higher Education in Morocco

Mohammed Baidada, ISGA Rabat, Morocco*
https://orcid.org/0000-0003-4043-1211

Khalifa Mansouri, Hassan II University, Morocco

Franck Poirier, Bretagne Sud University, France

ABSTRACT

In education, the needs of learners are different the majority of the time, as each has specificities in terms of preferences, performance, and goals. Recommendation systems have proven to be an effective way to ensure this learning personalization. Already used and tested in other areas such as e-commerce, their adaptation to the educational context has led to several research studies that have tried to find the best approaches with the best expected results. This article suggests that a hybridization of recommendation systems filtering methods can improve the quality of recommendations. An experiment was conducted to test an approach that combines content-based filtering and collaborative filtering. The results proved to be convincing.

KEYWORDS

Collaborative Filtering, Content-Based Filtering, E-Learning, Experiment, Hybrid Filtering, Recommender Systems

INTRODUCTION

The integration of new technologies in the educational systems has become inescapable. Learners find themselves confronting systems that provide specific pathways and tailored pedagogical contents suiting their learning needs and profiles (Garrido et al., 2016; Segal et al., 2019). Teachers invest within their reach several tools that could help them in their missions to take the most appropriate pedagogical decisions. Personalization is an essential element that differentiates online education from classical face-to-face teaching, which offers common content to a group of learners, without taking into account their specificities (Clément et al., 2014).

Recommendation systems (RSs) have been used and adapted in education as a means of offering each learner the educational resources best suited to his or her profile or needs, as is done in the field of e-commerce (Burke et al., 2011). According to the filtering methods, the RSs are based upon two essential techniques: the first focused on the specificities of the user (Herath & Jayarathne, 2018; Leblay, 2016), and the second focused on the preferences and tendencies of the group to which the user belongs (Salihoun et al., 2014; Tadlaoui et al., 2015).

In order to improve the quality of recommendations in education, the authors of this article have experimented a hybrid approach that combines the content-based and the collaborative filtering

DOI: 10.4018/IJWLTT.294573

*Corresponding Author

approaches (Baidada et al., 2018). To do this, a recommendation module was integrated into the Moodle platform, and then an experiment was conducted on a real case in online test. The results of this experiment are the subject of this article. Before presenting the experiment and its results, and doing an analysis and interpretation, the authors summarize in the next section, the general context of the work and a state of art on the personalization in the online learning environments (OLEs), RSs and their use in the field of education.

THEORETICAL BACKGROUND AND STATE OF THE ART

PERSONALIZATION IN OLES

In a classical teaching approach, the teacher is obliged to give the same pedagogical content to a group of students, without being able to take into account the differences between them in terms of levels and preferences. This becomes possible in OLEs, by personalizing activities and content to learners, by adapting the pace of teaching, and by considering their motivations (Clément et al., 2014). Personalization also consists of proposing content and learning paths adapted to learners, by taking into account their preferences and objectives (Bejaoui et al., 2017; Garrido et al., 2016; Herath & Jayarathne, 2018).

Several research studies have examined the proposal of personalization approaches in OLEs. It is often the personalization of content and learning pathways that are discussed (Bejaoui et al., 2017; Garrido et al., 2016; Herath & Jayara-thne, 2018; Klasnja-Milicevic et al., 2011). Works in this area have tried to rely on different concepts each time to try to propose efficient systems that are well adapted to specific contexts. Some researchers have suggested hypermedia to provide learners with the opportunity to navigate in the e-learning system according to their needs (Tsortanidou et al., 2017). Other researchers have relied on intelligent tutoring systems to provide personalized learning environments (Clément et al., 2014; Segal et al., 2019). These systems use Artificial Intelligence (AI) techniques to imitate the behavior of a human tutor. Note that AI approaches are strongly used to ensure the personalization of OLEs, given their predictive capacity. Mandin et al. (2015) proposed a skills-based model of personalization of learning. Cakula & Sedleniece (2013) used the principles of Knowledge Management to present a model of personalization based on ontologies.

Recommendation Systems in OLEs

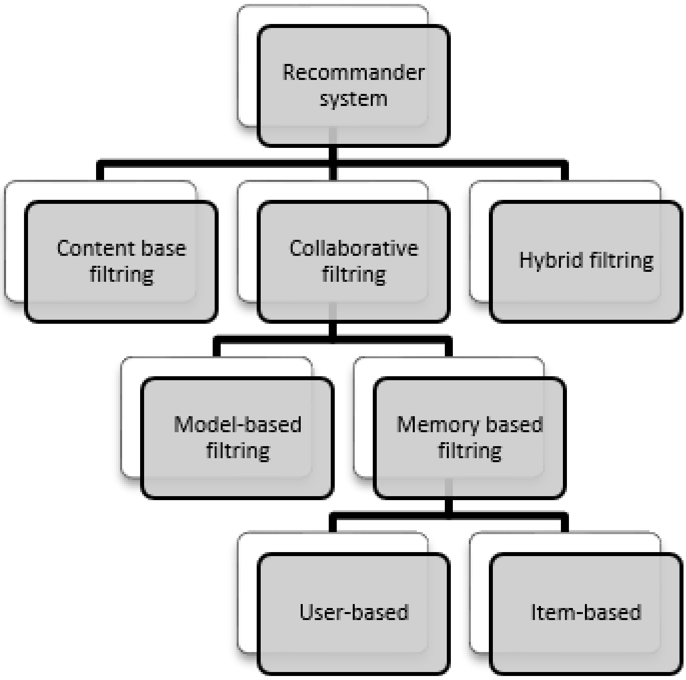
With the growth in the use of the web and the important data generated by interactions between users and systems, several important companies operating mainly in e-commerce (Amazon, Netflix, Ebay, Facebook, Twitter, LinkedIn, among others) have introduced more and more sophisticated RSs (Burke et al., 2011; Klasnja-Milicevic et al., 2011; Linden et al., 2007), by offering their users content that could potentially either interest them to retain or to encourage them to consume.

There are several definitions of RSs; according to Isinkaye et al. (2015): "Recommender systems are information filtering systems that deal with the problem of information overload by filtering vital information fragment out of large amount of dynamically generated information according to user's preferences, interest, or observed behavior about item".

There are several filtering methods, and several classifications have been given in the literature (Haydar, 2014; Lemdani, 2016; Tadlaoui et al., 2015). They essentially meet in the classification given by Isinkaye et al. (2015) (figure 1), whose description is as follows:

Content-based filtering: It is a technique that proposes to a user, taking into account his or her profile, the items having the same values corresponding to a set of attributes that describe them. A limitation of this technique is that it cannot present to the user the categories of items outside of those that he or she accustomed to consult. The problem can be solved with the following method.

Figure 1. Classification of filtering methods



Collaborative filtering: This technique considers the user in a group and proposes items that he or she has not evaluated before, but that other members of his or her group have already evaluated, we are talking here about memory-based filtering. This method can also make it possible to deduce what would be the evaluation of a user for an item if his or her group has already evaluated it; we are talking here about model-based filtering.

Note that in the case of the model-based filtering, we can consider the similarity between the users: user-based, or between the items evaluated by these users: item-based.

Hybrid filtering: The previous methods have some limitations, such as cold start or sparsity of data. These problems are often solved by the hybridization of two or more approaches. This hybridization also makes it possible to increase the quality of the recommendations.

Works on the Recommendations in the OLEs

In addition to e-commerce, the RSs have been integrated in other areas, especially in e-learning, with the aim of recommending resources and pedagogical activities best adapted to the learner's preferences and needs. RSs have emerged as an indispensable tool in the field of personalization in OLEs (Anaya et al., 2013; Berkani et al., 2013; Herath and Jayarathne, 2018; Klasnja-Milicevic et al., 2011; Tadlaoui et al., 2015; Tadlaoui, 2018).

Several studies have examined the use of RSs to propose the best approaches, often using algorithms based on artificial intelligence and machine learning. Portugal et al. (2017) conducted a study of the algorithms used in RSs, and affirmed that those based on Bayesian networks and decision trees are the most used. Several research studies have examined the implementation of RSs in an educational context. Berkani et al. (2013) experimented with a combination of several filtering approaches to provide learners with pedagogical resources based on their goals and needs.

Tadlaoui et al. (2015) proposed a recommendation system that uses social links to provide the most appropriate learning resources for a learner; they considered the most popular, most useful and most recently accessed resources.

DESCRIPTION OF THE APPROACH

Background

Klasnja-Milicevic et al. (2015) raised through a study of the state of the art the interest of recommender systems in learning environments as a tool for the personalization of educational processes. They recommended that a good RS is one that considers the learning style, interests and preferences of the learner, and also the value of taking into account the learner's social context to enrich recommendation decisions (Klasnja-Milicevic et al., 2015).

The research work presented in this article is inline with this; it attempts to verify the impact of taking into account the preferences of learners from an individual point of view, and of taking into account the preferences of the groups to which they belong, on the relevance of the recommendations that may be proposed to them. This research work is interested in the use of the RSs in order to adapt the learning resources proposed by the learning system to the profiles of the learners. It assumes that if the characteristics of an educational resource are close to the learner's preferences, they will be encouraged and interested in their learning process.

According to the review literature, the combination of several filtering approaches makes it possible to go beyond the limits of the filtering methods used separately, and also to improve the quality of the recommendations (Berkani et al., 2013; Burke, 2007; Isinkaye et al., 2015; Lemdani, 2016; Paradarami et al., 2017). Burke (2007) identifies several types of hybrid filtering, like:

- **Weighted:** The scores of the different recommendation approaches are weighted (combined numerically);
- **Switching:** The system chooses among the recommendation approaches and applies the selected one;
- **Mixed:** The recommendations of the different approaches are presented together;

As abovementioned, hybridization improves the quality of the recommendations, which is the aim of this study. The authors considered the two approaches of filtering associated with RSs, namely content-based filtering and collaborative filtering; their definitions were presented previously, and a weighted hybridization was used.

The approach is also based on the notion of the learner's profile and the standards of learning objects description presented below. The learner's preference component is one of the eight main components given by the most important models defining the learner's profile, which are: IEEE PAPI (Public and Private Information for Learners) and IMS LIP (Learner Information Package) (Pavlov & Paneva, 2006; Wei & Yan, 2009). They define the notion of the profile through the following elements: Personal information, Preference, Performance, Information session, Portfolio, Goal, Security and Relation information.

It was also necessary to make a choice of metadata that could describe the pedagogical resources that were to be the core of the exchanges between the learners in the system. The study of the standards for the Learning Object Metadata (LOM) revealed the three most important ones, which are IEEE LOM, CanCORE LOM and Dublin CoreMetadata (Roy et al., 2010). They described a learning object by the following elements: General, Life cycle, Meta-metadata, Technical, Educational, Rights, Relationship and Annotation. The authors selected three elements that are related to learner's preferences, namely General, Technical and Educational. The following table (table 1) gives more details on these selected elements and their possible values:

Table 1. Description of metadata retained for educational resources

Section	Element Retained	Values
General	Language	English, French, Arabic
Technical	Resource format	Video, Document (pdf, slides, …), Web article
Educational	Resource type	Course, Tests or exercises, Forum

To evaluate the approach, the authors carried out an experiment for which it was necessary to develop a platform that integrates and implements the three filtering methods, namely collaborative filtering, content-based filtering and hybrid filtering. This platform must integrate elements of course management and pedagogical activities, as well as a space for exchange between learners, in order to consider the social component of the approach, which consists of taking into account the context of the group to which the learner belongs.

Technical Description

The base platform used is Moodle version 3.2. It has been enriched by the installation of a plug-in named SocialWall, which allows changing the format of the courses by adopting "social network" view integrating the notions of post, comment and like. It was also necessary to introduce the modules of recommendations, which were developed separately, and integrated in the source code of Moodle. It was necessary to develop three modules relating to each selected filtering method:

- **Individual recommendation module:** relating to the content-based filtering method;
- **Social recommendation module:** relating to the collaborative filtering method;
- **Hybrid recommendation module:** relating to the hybridization of the two methods: content-based and collaborative filtering.

Note that in order to implement the chosen recommendation algorithms, it was necessary to overcome constraints related to the understanding of the software architecture of the Moodle platform. This required some customization, creating new tables and attributes, to satisfy the needs required for the implementation of our algorithms.

Figure 2 shows the architecture of the platform in the hybrid case:

The learning environment keeps the traces of the learners with the system, and also the traces of the exchanges between the learners. This is guaranteed by the social exchange module integrated into the platform. Thereafter, the recommendation modules rank the resources according to the implemented algorithm described below, and the arithmetic average of the two rankings will yield the final recommendations proposed to the learner.

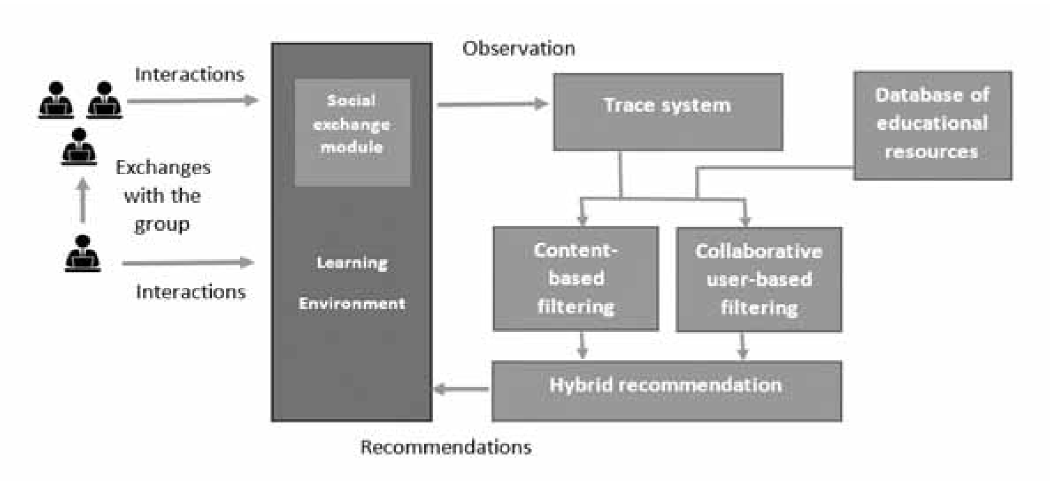
EXPERIMENTAL PROTOCOL

OBJECTIVE AND TYPE OF THE EXPERIMENT

The objective of this experiment is to evaluate a hybrid recommendation approach of pedagogical resources in an educational context. This approach considers both the individual characteristics of the learner and the links that connect the learner to his or her group, in order to propose the most appropriate pedagogical resources.

In their thesis Lemdani (2016) and Haydar (2014) present that there are essentially three methods of experimentation:

Figure 2. Platform architecture used for hybrid recommendation case



- **Offline test:** simulating algorithms on datasets, it has the advantage of being inexpensive in time, but it requires a dataset that must be well adapted to the experiment objectives;
- **User study:** with real users generally recruited and paid for the test, which can mitigate the credibility of the results;
- **Online test:** with users who use the system in real life situations, this gives better results but it is more time consuming.

With the difficulty of finding datasets adapted to the context of this study, the authors opted for an online test type; this had the disadvantage of being more expensive in time, but it guarantees better results.

TARGET GROUPS

The experiment targeted two groups of students in two different institutes of higher education in Morocco, the first is a group of 2nd year common core of engineering degree in a private institute, and the second is a group of 1st year of engineering cycle specialty in a public institute. The experiment started with an initial enrollment of 87 students, but stayed at 82 after eliminating 5 students who did not participate in the test. The average age of the group was 21.07 with a standard deviation of 1.32. There were 32% female and 68% male.

Each group was divided into three subgroups:

- **Subgroup 1:** to whom a content-based filtering approach has been proposed;
- **Subgroup 2:** to whom a collaborative filtering approach has been proposed;
- **Subgroup 3:** to whom a hybrid filtering approach has been proposed.

The following table (table 2) shows the number of participants selected for each subgroup:

Choice of Course and Duration of the Experiment

The students were enrolled in two different courses, relative to their level: an advanced programming techniques course for the private institute group, and an object-oriented programming course for the public institute group. Course materials were shared to force students to enter the platform, and to

Table 2. Distribution of groups

	Subgroup 1	Subgroup 2	Subgroup 3	Total
Public	19	21	21	61
Private	7	7	7	21
Total	26	28	28	82

be present in the social module and exchange educational resources with each other. The experiment was conducted between April 1 and May 15, 2019.

Functional Description

Each student could log into the platform with his or her account to access the course he or she was enrolled in. It should be remembered that the courses were presented under a "social network" view. Afterwards, the student could carry out the following actions:

- Add a post;
- Add a URL: associate to a post a URL link to an external resource;
- Give the description of resource characteristics after each link added. Table 3 presents the different possible values of these characteristics;
- Comment a post;
- Make a "like" or "dislike" on a post.

Table 3. Description of the characteristics of the resources and their possible values

Characteristic	Possible Values
Language	English, French, Arabic
Resource type	video, document, web article
Activity type	course, exercises, forum

For each student links appear to recommended resources. These links may change depending on the evolution of the exchanges.

Description of the Recommendation Algorithms Used

For the content-based recommendation

1. Constructing an Item/Attribute Matrix (called I): Each line of the matrix corresponds to the description of an item with respect to the various attributes selected; these attributes are "video", "document", "web article", "courses", "exercises and tests", "forum", "English", "French" and "Arabic". For example, to a video type English course item, will be associated the vector/line (1,0,0,1,0,0,1,0,0) which is a 9-dimensional vector with respect to the 9 characteristics mentioned above (figure 3).

Figure 3. Example of the item/attribute matrix

	Video	Document	Artweb	Course	Exercises	Forum	English	French	Arabic
item 1	0	1	0	0	1	0	0	1	0
item 2	1	0	0	0	1	0	0	1	0
item 3	0	1	0	1	0	0	1	0	0
item 4	1	0	0	1	0	0	1	0	0
item 5	0	0	1	1	0	0	0	1	0

2. Construction of a user vector (called U): For a given user will be assigned 1 to an item that he prefers (like), and 0 otherwise. For example, for a user who has evaluated the five items in the example in table 4, and has made "like" for items 1, 3 and 5, his or her vector U will be (1,0,1,0,1).
3. Construction of a user profile vector (called P): P = U * I, by multiplying the vector U by the matrix I. This vector profile, also a 9-dimentional vector, represents a projection of the user with respect to the criteria. For the example in table 4, and after calculation, P will be equal to (0,2,0,1,1,0,1,1,0).
4. Thereafter, a calculation of the Euclidean distances between P and each row of the matrix will be performed.
5. Using the k-nearest neighbors method (k-NN) (Adeniyi et al., 2014), the recommendation will correspond to the items with the lowest distance and other than those that the user prefers, i.e. the item vectors that are closely related to the vector P.

For the collaborative filtering recommendation

1. Constructing a User/Item matrix: it represents a score for each user in relation to each item (figure 4). In general, this score can be assigned by the user; it can also be the number of accesses, the duration of access, etc. In the experiment, the authors chose the appreciation given by users to the articles with like/dislike mode (Shi et al., 2014).

Figure 4. Example of the user/item matrix

	Item1	Item2	Item3	Item4	Item5	Item6	Item7
User A	1			1	1		
User B	1	1	1				
User C				1	1	1	
User D		1					1

2. The Euclidean distances between the users (the rows of the matrix) are calculated.
3. Minimum distances are considered.
4. The recommendation will correspond to scores calculated by the following formula:

$$\text{Score }(U_i\text{, item}) = \frac{\sum_j distance\left(U_i,\ U_j\right) * score(U_j, item)}{\sum_j \left|distance\left(U_i,\ U_j\right)\right|}$$

For the hybrid filtering recommendation

The distances relative to the items according to hybrid filtering is the average of the distances generated by the two previous filtering methods.

EVALUATION OF THE EXPERIENCE

Evaluation Method

Through the exchange of resources on the platform, four classes of data have been generated relative to the educational resources:

- The recommended resources (generated by the algorithm);
- The relevant recommended resources (generated by the algorithm and appreciated by learners);
- Resources not recommended (not generated by the algorithm);
- Relevant resources not recommended (not generated by the algorithm and appreciated by learners).

To evaluate the recommendation system, the three main indicators used in these contexts were considered (Burke, 2007; Isinkaye et al., 2015; Portugal et al., 2017; Roy et al., 2010), namely:

- **Precision**: the number of relevant recommended resources (like) found relative to the total number of recommended resources:

$$\frac{Number\ \ of\ \ relevant\ \ resources\ \ recommended\left(like\right)}{Number\ \ of\ \ resources\ \ recommended}$$

- **Recall**: the number of relevant recommended resources (like) found relative to the total number of relevant resources:

$$\frac{Number\ \ of\ \ relevant\ \ resources\ \ recommended\ \left(like\right)}{Number\ \ of\ \ relevant\ \ resources\ \left(like\right)}$$

- **F-measure**: it combines the two indicators into a harmonic mean:

$$2 * \frac{precision * recall}{precision + recall}$$

Precision represents accuracy and quality, while Recall represents completeness and quantity. The F-measure represents a harmonic mean because precision and recall are ratios.

The data collected were presented in a similar table (table 4):

Table 4. Model of the table of indicators obtained

	Qualitative variables		Quantitative variables		
Student	**Institute**	**Group**	**Precision**	**Recall**	**F-measure**
Student i	Private or Public	G1 or G2 or G3	Value	Value	Value

ANALYSIS METHODS

To evaluate the experiment, the authors used the SPSS software and selected the methods of analysis presented below:

Analysis of variance (ANOVA)

The analysis of variance, called ANOVA, aims to test the significant differences between the averages. This method is used when we want to measure the effect and influence of one or more qualitative variables on a continuous variable.

In variance analysis, we try to explain the variations of a metric variable by one or more nominal explanatory factors. Its principle is to test the equality of averages of several normal populations.

In the case of the one-way analysis of variance, called ANOVA1, we try to explain the variations of a single dependent metric variable by a single explanatory factor.

As part of the empirical study, the authors try to test the effect of the variable "Group" (qualitative variable) on each of the quantitative variables namely Precision, Recall and F-measure. In other words, they explain the variations of each indicator according to the factor "Group". It is therefore a question of comparing the three subgroups each time for an indicator. This justifies the use of one-way analysis of variance (ANOVA1).

ANOVA1 was so used to compare the 3 subgroups of the experiment, considering the qualitative variable "Group". An initial analysis was made for all students in both institutes. Then, the same analysis was employed for each institute separately.

Student T-test

Student T-test is a statistical test that makes it possible to compare the averages of only two groups. It is to know if the averages of the two groups are statistically different.

The purpose of this test is to compare the means of two populations using two samples. For this experiment, it is a question of comparing the two public and private institutes each time relatively to an indicator by considering the qualitative variable "Institute".

RESULTS AND INTERPRETATIONS

In this section, the authors will present the results obtained and their interpretations. First, an ANOVA1 analysis was used to compare the three subgroups across the two institutes, and then for each institute separately. At the end, by using the Student T-test, a comparison between the two institutes was made.

The formulation of the null hypothesis was used. It is a question of globally testing the equality of the averages of the three subgroups.

- H0: there is no significant difference between the three subgroups.
- H1: at least one subgroup is different from the others.

In an ANOVA1 analysis, and to compare between subgroups, the Tukey test is used. It is based on a significance threshold (Tukey significant difference called sig) of 5% (0.05). If the significance threshold obtained is less than 5%, then the null hypothesis H0 is rejected and the hypothesis H1 is retained, i.e. at least one subgroup is different from the others.

ANOVA1 FOR THE TWO INSTITUTES (PUBLIC AND PRIVATE)

Analysis of the three variables Precision, Recall and F-measure

Using SPSS software, the intergroup analysis of the three variables Precision, Recall and F-measure, for the two grouped institutes gave a significance level (sig) of 0.000, which leads to conclude that the Precision indicator is on average not identical in all three subgroups. The null hypothesis H0 is therefore rejected. The hypothesis H1 is then retained, and it was necessary to know the subgroup or subgroups that is or are different, making a multiple comparison of means.

Multiple comparisons of means

When the analysis of variance test is significant, we must conclude that there are important differences between some of the averages of these normal populations. In this case, the multiple comparisons of means seeks to determine a ranking of the means by indicating the significant differences.

Table 5. Multiple comparisons of the three variables (Precision, Recall, F-measure) - the two institutes combined

	Sig (G1 vs G2)	**Sig (G1 vs G3)**	**Sig (G2 vs G3)**
Precision	0.127	0.000	0.001
Recall F-measure	0.830 0.529	0.000 0.000	0.000 0.000

According to the table of multiple comparisons and the Tukey method, significance below the threshold of 0.05 makes it possible to identify the subgroups that give different results. According to Table.5 that summarizes the results for the three indicators, the three subgroup compared to the other two subgroups 1 and 2 has a significance level (sig) less than 0.05.

A classification in homogeneous subsets was subsequently made, to find those with similarities and those that stand out. The analysis for the three indicators give a result that distinguishes 2 subsets, the first one composed of subgroups 1 and 2 for which there is no significant difference, and the second one composed of subgroup 3 which has a higher average (Table 6).

Table 6. Distribution into homogeneous subsets for three variables (Precision, Recall, F-measure) - the two institutes combined

		Precision		**Recall**		**F-measure**	
		Subset		**Subset**		**Subset**	
Subgroups	**Size of subgroup**	**1**	**2**	**1**	**2**	**1**	**2**
Subgroup 1	26	0.38		0.23		0.29	
Subgroup 2	28	0.45		0.24		0.31	
Subgroup 3	28		0.57		0.32		0.41

This allows us to conclude that for all indicators, the subgroup 3 differs from the other two subgroups.

ANOVA1 FOR THE PUBLIC INSTITUTE

As previously presented, an ANOVA1 analysis was conducted for each institute separately.

In the case of the public institute, the inter-group analysis of the three indicators Precision, Recall and F-measure gave a significance level equal to 0.000 each time, so the null hypothesis was rejected, and it was necessary to determine the subgroup that stands out.

Table 7. Multiple comparison of the three variables (Precision, Recall, F-measure) – Public institute

	Sig (G1 vs G2)	Sig (G1 vs G3)	Sig (G2 vs G3)
Precision	0.330	0.000	0.001
Recall	0.990	0.000	0.000
F-measure	0.904	0.000	0.000

For the three variables, the subgroup 3 has a different mean value compared to the other two subgroups 1 and 2 (Table 7).

The comparison of harmonic means also gives a distinction for subgroup with an average of 0.61 for the Precision variable, 0.35 for the Recall variable and 0.44 for the F-measure variable (Table 8). With respect to the classification into homogeneous subsets, the analysis always gives the subgroup 3 in one subset and the two subgroups 1 and 2 in another (Tables 8).

Table 8. Distribution into homogeneous subsets for three variables (Precision, Recall, F-measure) - public institute

		Precision		Recall		F-measure	
		Subset		Subset		Subset	
Subgroups	**Size of subgroup**	**1**	**2**	**1**	**2**	**1**	**2**
Subgroup 1	19	0.41		0.24		0.30	
Subgroup 2	21	0.46		0.24		0.31	
Subgroup 3	21		0.61		0.35		0.44

This allows us to conclude that for the three Precision, Recall and F-measure indicators, subgroup 3 is distinct each time from the other two subgroups 1 and 2.

ANOVA1 FOR THE PRIVATE INSTITUTE

For the private institute, the ANOVA1 analysis showed a significant difference greater than the 5% threshold (0.68, 0.246, and 0.161 respectively for the Precision, Recall and F-measure variables). This means that the hypothesis H0 is retained and that the 3 subgroups do not show any difference. This is confirmed by the multiple comparisons. The homogeneous subset distribution also put the three subgroups in a same subset (Table 9).

Table 9. Distribution into homogeneous subsets for three variables (Precision, Recall, F-measure) - private institute

		Precision	Recall	F-measure
		Subset	Subset	Subset
Subgroups	Size of subgroup	1	1	1
Subgroup 1	7	0.31	0.19	0.24
Subgroup 2	7	0.41	0.24	0.31
Subgroup 3	7	0.47	0.26	0.33

For the private institute, there is no difference between the subgroups. This may be due to the reduced size of the three subgroups.

STUDENT T-TEST BETWEEN THE TWO INSTITUTES

As has been presented before, to consider the qualitative variable “Institute” and compare between the two private and public institutes, Student T-test was used. The results are presented below.

The purpose of this test is to verify whether the average of an indicator for the private institute is or is not equal to the average of the same indicator for the public institute.

The null hypothesis formulation was also used to test the equality of means.

Table 10. Student T-test for precision, recall and F-measure indicators

		Sig
Precision	equal variances hypothesis unequal variances hypothesis	0.007 0.006
Recall	equal variances hypothesis unequal variances hypothesis	0.025 0.020
F-measure	equal variances hypothesis unequal variances hypothesis	0.016 0.013

According to the results provided by the SPSS software, for all three indicators, the significance threshold (sig) is less than 5% (Table 10), which leads us to reject the null hypothesis H0 and conclude that for the three indicators there is a difference between the two institutes.

Table 11. Group statistics

	Institute	Size	Average	Standard deviation	Mean standard error
Precision	Private Public	21 61	0.40 0.50	0.13 0.14	0.03 0.02
Recall	Private Public	21 61	0.23 0.28	0.07 0.08	0.02 0.01
F-measure	Private Public	21 61	0.29 0.35	0.92 0.10	0.02 0.01

According to the table of group statistics (Table 11), the values of the three indicators are higher, on average, for the public institute. Especially the precision, which presents an interesting difference (0.50 compared to 0.40). Since the precision reflects the quality of the recommendations, this can be explained by the fact that the students of the public institute have often a better level and have a certain maturity, which has been reflected in their reaction to the resources exchanged on the platform, being more careful with regard to the choice and evaluation of shared resources.

DISCUSSION

The experiment aimed to compare three methods of recommendation filtering: content-based filtering, collaborative filtering and hybrid filtering, in both a public and private institute. In each institute, the students were divided into three subgroups, each corresponding to a filtering approach. The analysis focused on three indicators: Precision, which reflects the proportion of appreciated resources (like), Recall, which reflects the proportion of relevant recommendations relative to relevant resources, and F-measure, which is a harmonic mean of the two previous indicators.

The results of the experiment showed that by considering the distribution of the three subgroups on both private and public institute, and by conducting an analysis of the impact of the qualitative variable “Group” on the three indicators, subgroup 3 is clearly distinct from the other two subgroups 1 and 2. This confirms that the hybrid filtering approach conducted for subgroup 3 gave better results for all three indicators.

The analysis was repeated on each institute separately. For public institute, the same results was obtained, the hybrid filtering provides more relevant recommendations. For the private institute, the three approaches have produced almost equivalent results; which may be due to the small number of students considered for this institute, only seven students per subgroup in the private institute compared to 21 in the public institute.

Regarding the analysis of the impact of the qualitative variable “Institute” on the three indicators, the values of the three indicators are on average higher among students at the public institute. It is especially the precision that presents a significant difference. The level of students from public institutes, which is globally better in our Moroccan context, may be a factor that led them to be more relevant both in terms of resources sharing and in their evaluation of the educational resources (like).

FUTURE WORK

The convincing results of this experiment encourage us to improve our approach and to carry out future work, consisting essentially of:

- Considering other modes of evaluation of educational resources by learners. First, we plan to test other explicit evaluation modes: replace the binary mode based on like/dislike by a multi-value mode based on a voting system. Then we can test other modes of implicit evaluation, by analyzing the comments written by the learners, and thus exploit the social component, which is of particular interest for our approach. This analysis can use text-mining techniques such as TF-IDF (Wang et al., 2014). We can also consider other criteria such as the number and time of access to resources.
- Extending the basis of the recommendations by considering other elements that define the learner’s profile, outside of the “preferences” component considered for this contribution, and that may have a greater pedagogical impact, namely, the “performance” and “goals” components. In this sense, we can develop a system based on intelligent tutors capable of determining or predicting the learner’s needs and proposing the most appropriate resources and activities (Hafidi et Mahnane, 2018).

This work is therefore a first draft that can lead to many extensions with the objective of improving personalization techniques in an online learning environment.

CONCLUSION

This article uses an experiment to determine whether hybridizing content-based and collaborative filtering methods can improve the relevance of recommendations in an online educational context.

The results demonstrated that the hybrid recommendation approach works best when considering the public institute alone and when considering the public and private institutes together. It can be concluded that taking into account both the individual and social specificities of a learner, can improve the relevance of the recommendations of educational resources in an e-learning environment.

The use of RSs can be an important tool for personalizing learning. Research in this area remains open to explore the panoply of existing methods and approaches of recommendation to find those that can assist in the pedagogical process and enhance personalization in e-learning environments. It would also be interesting to explore other elements defining the learner profile besides preferences, such as performance and goals.

Several perspectives are planned in the extension of this work. An evaluation of the resources on a scale of 1 to 5 instead of a binary evaluation (like or dislike), may be considered to have a more detailed appreciation. The inclusion of persuasive devices will also be an advantage to encourage participating learners to become more involved in the experience, such as earning badges after getting a good evaluation by a third party. It is also planned to use the enriched database of learners' profiles to suggest external resources matching their preferences.

REFERENCES

Adeniyi, D. A., Wei, Z., & Yongquan, Y. (2014). Automated web usage data mining and recommendation system using K-Nearest Neighbor (KNN) classification method. *Applied Computing and Informatics*, *12*(1), 90–108. doi:10.1016/j.aci.2014.10.001

Anaya, A. R., Luque, M., & García-Saiz, T. (2013). Recommender system in collaborative learning environment using an influence diagram. *Expert Systems with Applications*, *40*(18), 7193–7202. doi:10.1016/j.eswa.2013.07.030

Baidada, M., Mansouri, K., & Poirier, F. (2018). Hybrid Recommendation Approach in Online Learning Environments. In Á. Rocha & M. Serrhini (Eds.), *Information Systems and Technologies to Support Learning. EMENA-ISTL 2018. Smart Innovation, Systems and Technologies* (Vol. 111). Springer., doi:10.1007/978-3-030-03577-8_5

Bejaoui, R., Paquette, G., Basque, J., & Henri, F. (2017). Cadre d'analyse de la personnalisation de l'apprentissage dans les cours en ligne ouverts et massifs (CLOM). *Sciences et Technologies de l'Information et de la Communication pour l'Éducation et la Formation*, *24*(2), 37–63. doi:10.3406/stice.2017.1739

Berkani, L., Nouali, O., & Chikh, A. (2013). Recommandation personnalisée des ressources dans une communauté de pratique de e-learning. Une approche à base de filtrage hybride. *INFORSID 2013: Proceeding of Informatique des organisations et systèmes d'information et de décision conference*, 131-138.

Burke, R. (2007). Hybrid Web Recommender Systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), Lecture Notes in Computer Science: Vol. 4321. *The Adaptive Web*. Springer. doi:10.1007/978-3-540-72079-9_12

Burke, R. D., Felfernig, A., & Göker, M. H. (2011). Recommender Systems: An Overview. *AI Magazine*, *32*(3), 13–18. doi:10.1609/aimag.v32i3.2361

Cakula, S., & Sedleniece, M. (2013). Development of a Personalized E-Learning Model Using Methods of Ontology. *Procedia Computer Science*, *26*, 113–120. doi:10.1016/j.procs.2013.12.011

Clément, B., Roy, D., Lopes, M., & Oudeyer, P. Y. (2014). *Online Optimization and Personalization of Teaching Sequences*. DI: Digital Intelligence - 1st International conference on digital cultures, Nantes, France.

Garrido, A., Morales, L., & Serina, I. (2016). On the Use of Case-Based Planning for E-learning Personalization. *Expert Systems with Applications*, *60*, 1–15. doi:10.1016/j.eswa.2016.04.030

Hafidi, M., & Mahnane, L. (2018). Implementing flipped classroom that used an intelligent tutoring system into learning process. *Computers & Education, 124*, 62-76. 10.1016/j.compedu.2018.05.011

Haydar, C. A. (2014). *Les systèmes de recommandation à base de confiance* (PhD Thesis). Lorraine University, Nancy, France.

Herath, D., & Jayarathne, L. (2018). Intelligent Recommendations for e-Learning Personalization Based on Learner's Learning Activities and Performances. *International Journal of Computer Science and Software Engineering*, *7*(6), 130–137. doi:10.13140/RG.2.2.27785.34406

Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian Informatics Journal*, *16*(3), 261–273. doi:10.1016/j.eij.2015.06.005

Klašnja-Milićević, A., Ivanović, M., & Nanopoulos, A. (2015). Recommender systems in e-learning environments: A survey of the state-of-the-art and possible extensions. *Artificial Intelligence Review*, *44*(4), 571–604. doi:10.1007/s10462-015-9440-z

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education*, *56*(3), 885–899. doi:10.1016/j.compedu.2010.11.001

Leblay, J. (2016). Aide à la navigation dans les parcours d'apprentissage par reconnaissance de procédés et recommandations à base de traces. RJC-EIAH: Rencontres Jeunes Chercheurs Environnements Informatiques pour l'Apprentissage Humain, Montpellier, France.

Lemdani, R. (2016). *Système hybride d'adaptation dans les systèmes de recommendation* (PhD Thesis). Paris-Saclay University, Paris, France.

Linden, G., Smith, B., & York, J. (2003). Amazon.com Recommendations Item-to-Item Collaborative Filtering. *IEEE Internet Computing*, *7*(1), 76–80. doi:10.1109/MIC.2003.1167344

Mandin, S., Guin, N., & Lefevre, M. (2015). Modèle de personnalisation de l'apprentissage pour un EIAH fondé sur un référentiel de compétences. EIAH'2015, 7ème Conférence sur les Environnements Informatiques pour l'Apprentissage Humain, 126-137.

Paradarami, T. K., Bastian, N. D., & Wightman, J. L. (2017). A hybrid recommender system using artificial neural networks. *Expert Systems with Applications*, *83*, 300–313. doi:10.1016/j.eswa.2017.04.046

Pavlov, R., & Paneva, D. (2006). Personalized and Adaptive Learning – Approaches and Solutions. *Proceedings of the Third CHIRON Open Workshop "Visions of Ubiquitous Learning",* 2-13.

Portugal, I., Alencar, P., & Cowan, D. (2017). The Use of Machine Learning Algorithms in Recommender Systems: A Systematic Review. *Expert Systems with Applications*, *97*, 205–227. doi:10.1016/j.eswa.2017.12.020

Roy, D., Sarkar, S., & Ghose, S. (2010). A Comparative Study of Learning Object Metadata, Learning Material Repositories, Metadata Annotation & an Automatic Metadata Annotation Tool. *Advances in Semantic Computing*, *2*, 103-126.

Salihoun, M., Guerouate, F., & Sbihi, M. (2014). The exploitation of traces serving tutors for the reconstruction of groups within aCBLE. *Procedia: Social and Behavioral Sciences*, *152*, 219–226. doi:10.1016/j.sbspro.2014.09.184

Segal, A., Gal, K., Shani, G., & Shapira, B. (2019). A difficulty ranking approach to personalization in E-learning. *International Journal of Human-Computer Studies*, *130*, 261–272. doi:10.1016/j.ijhcs.2019.07.002

Sharma, M., & Mann, S. (2013). A Survey of Recommender Systems: Approaches and Limitations. *International Journal of Innovations in Engineering and Technology*.

Shi, Y., Larson, M., & Hanjalic, A. (2014). Collaborative Filtering beyond the User-Item Matrix A Survey of the State of the Art and Future Challenges. *ACM Computing Surveys*, *47*(1), 3. Advance online publication. doi:10.1145/2556270

Tadlaoui, M. (2018). *Système de recommandation de ressources pédagogiques fondé sur les liens sociaux: formalisation et évaluation* (PhD Thesis). INSA Lyon, Lyon University, Lyon, France, in partnership with Tlemcen University, Tlemcen, Algeria.

Tadlaoui, M., George, S., & Sehaba, K. (2015). Approche pour recommandation de ressources pédagogiques basée sur les liens sociaux. EIAH'2015 7ème Conférence sur les Environnements Informatiques pour l'Apprentissage Humain, 192-203.

Tsortanidou, X., Karagiannidis, C., & Koumpis, A. (2017). Adaptive Educational Hypermedia Systems based on Learning Styles: The Case of Adaptation Rules. *International Journal of Emerging Technologies in Learning, 12*(5), 150-168. 10.3991/ijet.v12i05.6967

Wang, N., Abel, M., Barthès, J., & Negre, E. (2014). Towards a Recommender System from Semantic Traces for Decision Aid. *Proceedings of the International Conference on Knowledge Management and Information Sharing - KMIS*, 274-279. 10.5220/0005133502740279

Wei, X., & Yan, J. (2009). Learner Profile Design for Personalized E-Learning Systems. *2009 International Conference on Computational Intelligence and Software Engineering*, 1-4. doi:10.1109/CISE.2009.5363560