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Hybrid Filtering Recommendation System in an Educational Context: Experiment in higher education in Morocco

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Abstract: In education, the needs of learners are different in the majority of the time, as each has specificities in terms of preferences, skills 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. Believing that a hybridization of recommendation systems filtering methods can improve the quality of recommendations, we have conducted an experiment to test an approach that combines content-based filtering and collaborative filtering. The results proved to be convincing.

Keywords: E-learning; Recommender system; Content-based filtering; Collaborative filtering; Hybrid filtering; Experiment.

Reference to this paper should be made as follows: Author. (xxxx) 'Title', *Int. J. xxxxxxxx xxxxxxxx*,

Biographical notes:

1 Introduction

The use of new technologies in education systems has become an unavoidable reality. Learners find themselves in front of systems able to help them in their learning scenarios, or even guide them by presenting them the pathways to follow as well as the pedagogical contents best suited to their needs and their profiles (Garrido et al., 2016; Segal et al., 2019). Teachers, for their part, find within their reach tools that can help them in their missions to make 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 learner, without taking into account their specificities (Clément et al., 2014).

Recommendation systems (RSs) have been used and adapted in the field of 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 on two essential techniques: the first focused on the specificities of the user (Herath and Jayarathne, 2018; Leblay, 2016), and the second focused on the preferences and tendencies of the group to which the user belongs (Salihouna et al., 2014; Tadlaoui et al., 2015).

In order to improve the quality of recommendations in the field of education, we have experimented a hybrid approach that combines the two filtering approaches previously mentioned (Baidada et al., 2018). To do this, we developed a recommendation module that was integrated into the Moodle platform, and then we experimented our approach on a real case in online test. The results of this experiment are the subject of this article. Before spreading our experimentation and its results, and doing an analysis and interpretation, we summarize in the next section, the general context of our work and a state of the art on the personalization in the online learning environments (OLEs), and RS and their use in the field of education.

2 Theoretical background and state of the art

2.1 Personalization in OLEs

On the one hand, in a classical teaching approach the teacher is obliged to give the same educational content to a group of student, without being able to take into account the differences between them in terms of levels and preferences. On the other hand, this becomes possible in OLEs, by personalizing activities and content to learners, by adapting the pace of teaching to them, 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, skills and also their objectives (Bejaoui et al., 2017; Garrido et al., 2016; Herath and 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 and Jayarathne, 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 tutors to provide personalized learning environments (Clément et al., 2014; Segal et al., 2019). Mandin et al. (2015) proposed a skills-based model of personalization of learning. Cakula et al. (2013) used the principles of Knowledge Management to present a model of personalization based on ontologies.

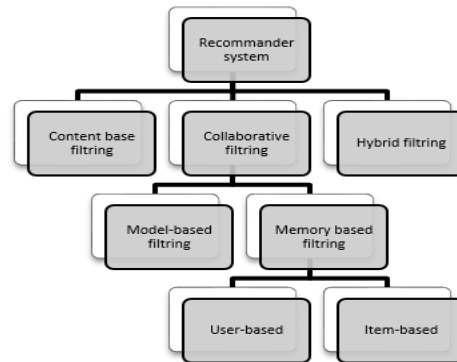
2.2 Recommendation systems in OLEs

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

There are several definitions of RS, according to Sharma et al. (2013): “Recommendation System is an intelligent system that makes suggestion about items to users that might interest them”. Isinkaye et al. (2015) give a similar definition evoking the filtering aspect: “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, of which 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), whose description is as follows:

Figure 1 Classification of filtering methods



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.

Collaborative filtering: this technique considers the user in a group setting, and proposes items that he or she has not evaluated before, but that other members of his or her group have already evaluated. The objective of this filtering method can be either to propose to the user items that he or she has never evaluated, or also to deduce what would be the evaluation of a user for an item if it has already been evaluated by his or her group. This distinction leads us to define two sub-categories: memory-based filtering for the first case, and model-based filtering for the second one.

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 limitation, such as cold start or sparsity of data. These problems are often mitigated by the hybridization of two or more approaches. This hybridization also makes it possible to increase the quality of the recommendations, which is the objective of our work.

2.3 Works on the recommendations in the OLEs

In addition to e-commerce, the recommendation RSs have been integrated in other areas, notably in e-learning, with the aim of recommending resources and pedagogical activities that will be best adapted to the preferences and learner 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 research studies have examined the use of RS to propose the best approaches. Often it is the algorithms based on artificial intelligence and machine learning that have been used in RS. Portugal et al. (2017) conducted a study of the algorithms used in RS, and claimed that those based on Bayesian networks

and decision trees are the most used. Several research studies have examined the implementation of RS 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.

3 Description of our approach

3.1 Background

Our research work fits in with the context of personalization in OLEs. For a better personalization, we were interested in the use of the RS in order to approach the learning resources proposed by the learning system to the profiles of the learners and their preferences. We assume that if the characteristics of an educational resource are close to the learner's preferences, they will be encouraged in their learning process by being more comfortable.

According to the literature review, the combination of several filtering approaches makes it possible to go beyond the limits of the filtering methods used separately, but 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 seven types of hybrid filtering in the literature:

- **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.
- **Feature Combination:** The characteristics derived from the different approaches are combined and given to a unique recommendation algorithm.
- **Feature Augmentation:** One recommendation technique is used to compute a feature or set of features, which is the input to the next technique.
- **Cascade:** this method consists of applying successive recommendation approaches. Each approach proposes a set of candidate items for the next one.
- **Meta-level:** One recommendation technique is applied and produces results that enrich the input of the following technique.

As we have already presented, hybridization makes it possible to overcome the limitations of the different approaches, but also to improve the quality of the recommendations, which is our goal, we started from the two approaches of filtering associated with RSs, namely content-based filtering and collaborative

filtering; their definitions were presented previously, and we considered a weighted hybridization.

Our approach is also based on the notion of the learner 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 profile which are: IEEE PAPI (Public and Private Information for Learners) and IMS LIP (Learner Information Package) (Pavlov and Paneva, 2006; Wei and 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 our 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.

We have selected three elements that are related to learner's preferences, namely General, Technical and Educational. The following table gives more details on our choices of these elements by specifying 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 our approach, we carried out an experimentation 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 should integrate the elements that are usually found in any e-learning platform, in terms of course management and pedagogical activities as well as a space for exchange between learners so that we can consider the social component of our approach to consider the learner in the context of the group to which he belongs.

The following sections will be dedicated to a technical description of the platform and to a presentation of the experimental protocol.

3.2 Technical description

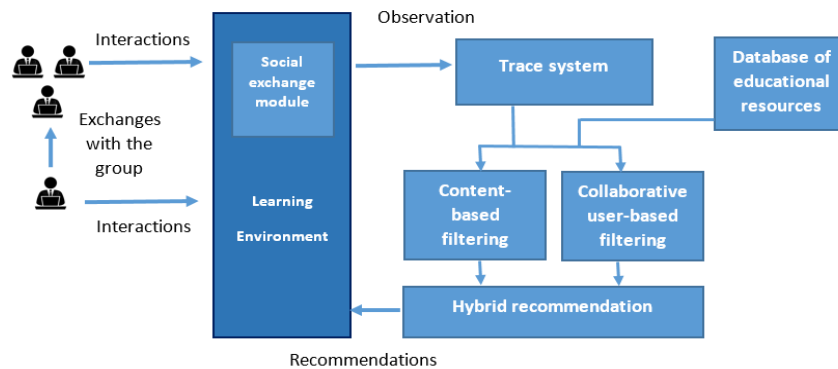
The basic platform is Moodle version 3.2. It has been enriched by the installation of the SocialWall plug-in which allows changing the format of the courses by adopting "social network" view integrating the notions of post, comment and like. It was also necessary to introduce the modules of recommendations which

were developed separately, then integrated in the source scripts 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.

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

Figure 2 Platform Architecture Used for Hybrid Recommendation Case



The learning environment keeps the traces of the learners with the system, and also the traces of the exchanges between 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 an arithmetic mean of the two rankings will result in the final recommendations proposed to the learner.

4 Experimental protocol

4.1 Objective and type of experiment

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

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

- 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 is more time consuming.

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

4.2 Target groups

The experiment has targeted two groups of students in two different institutions of higher education in Morocco, the first is a 2nd year common core group of engineering degree in a private institution, and the second is a 1st year group of engineering cycle specialty in a public institution. We 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: recommendations based on content-based filtering;
- Subgroup 2: recommendations based on collaborative filtering;
- Subgroup 3: recommendations based on hybrid filtering.

The following table gives an idea of the final distribution in terms of numbers:

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

4.3 Choice of course

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

to be present in the social module. It is through this module that they must exchange educational resources with each other.

4.4 Duration of the experiment

The experiment was conducted in the second half of 2018/2019 between April 1 and May 15, 2019.

4.5 Functional description

Each student could login to the platform with his or her account to access the course he or she was enrolled in. Let us reiterate that the courses were presented under a "social network" view. Afterwards he or she could carry out the following actions (figure 3):

- Add a post
- Add a URL: In a post, add a URL link to an external resource that he or she found interesting
- add the description of resource characteristics after each link added. Table 3 presents the different possible values of the 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

Figure 3. Interface for adding posts and links to resources

The screenshot shows a form for creating a post. At the top, there is a blue 'Post' button and an 'Editer le j' link. Below is a text area with the placeholder 'Poster un statut ou une note' and the content 'Voici, chers collègues, une série d'exercices en java sur l'héritage pour débutants'. There is a dropdown for 'Tous les participants' and buttons for 'Uploader un fichier' and 'Ajouter une URL'. The 'Collez ici le lien de la ressource' section has a text input for the URL (http://www.normalesup.org/~ramanana/teaching/3poo/TD5corr.pdf) and a 'Choisir un lien...' button. The 'Donnez ici le titre de la ressource' section has a text input with 'Série d'exercices - Classes et Héritage'. The 'Donnez ici la description de la ressource' section has radio buttons for 'Type ressource' (Video, Pdf, Doc, Ppt, Article Web) and 'Type activite' (Cours, Exercices et Tests, Forum). The 'Langue' section has radio buttons for 'Français', 'Anglais', and 'Arabe'.

For each student appear links to recommended resources (figure 4). These links may change depending on the evolution of the exchanges.

Figure 4. Interface of links to recommended resources

The screenshot shows a post by a user with a redacted name, posted on 'mardi 2 avril 2019, 15:17 à Tous les participants'. The URL is 'https://openclassrooms.com/fr/courses/1894236-programmez-avec-le-langage-c'. Below the URL, there are 9 likes and 3 comments. The first comment says 'intéressant , Merci.' and the second says 'Merci'. Below the comments, there is a section titled 'Ressources recommandées :' with three links: '1. POO en C++ (Article Web-Cours-Français)', '2. Concept programmation dans c++ (Vidéo-Cours-Français)', and '3. Cours Apprendre le C++ gratuit en PDF (pdf-Exercices ou tests-Français)'.

4.6 Description of the recommendation algorithms used

4.6.1 For the content-based recommendation

1. Constructing an Item/Attribute Matrix (it will be 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 element, of course, we will associate 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.

Table 4. 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 (we will call it U): For a given user (the one who is connected) we will assign 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 (we will call it P): $P = U * I$, by multiplying the vector U by the matrix I. This vector profile, also a 9-dimensional 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. Then we proceed to the calculation of the Euclidean distances between P and each of the lines of the matrix I.

5. Using the k nearest neighbors method (k-NN) (Adeniyi et al., 2016), 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 most closely related to the vector P.

4.6.2 For the collaborative filtering recommendation

1. Constructing a User/Item matrix: it represents for each user in relation to each item a score. In general, this score can be assigned by the user; it can also be the number of accesses, the duration of access, etc. In our experiment, we chose the number of accesses to the items (Shi et al., 2014).

Table 5. 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. We calculate the Euclidean distances between the users (the rows of the matrix).

3. Minimum distances are considered.

4. The recommendation will correspond to scores calculated by the following formula:

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

4.6.3. 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.

5 Evaluation of the experience

5.1 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 the learner);
- Resources not recommended (not generated by the algorithm);
- Relevant resources not recommended (not generated by the algorithm and appreciated by the learner).

To evaluate our referral system, we have based ourselves on the three main indicators used in these contexts (Burke, 2007; Isinkaye et al., 2015; Portugal et al., 2017; Roy et al., 2010), namely:

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

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

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

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

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

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

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 6. Table of Indicators Obtained

Student	Qualitative variables		Quantitative variables		
	Institution	Group	Precision	Recall	F-measure
Student 1	Private	G1	0.25	0.16	0.19
...
Student i	Private	G1	0.29	0.18	0.22
Student i+1	Private	G2	0.27	0.16	0.20
...
Student j	Private	G2	0.45	0.27	0.34
Student j+1	Private	G3	0.43	0.24	0.31
...
Student k	Private	G3	0.52	0.29	0.37
Student k+1	Public	G1	0.45	0.27	0.34
...
Student l	Public	G1	0.35	0.21	0.27
Student l+1	Public	G2	0.62	0.32	0.42
...
Student m	Public	G2	0.62	0.32	0.42
Student m+1	Public	G3	0.40	0.23	0.29
...
Student 82	Public	G3	0.56	0.32	0.41

5.2 Analysis Methods

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

5.2.1 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 to explain.

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 our empirical study, we try to test the effect of the group variable (qualitative variable) on each of the quantitative variables namely Precision, Recall and F-measure. In other words, we explain the variations of each indicator according to the group factor. It is therefore a question of comparing the three groups each time compared to an indicator. This justifies the use of one-way analysis of variance (ANOVA1).

We used ANOVA1 to compare the 3 subgroups of the experiment, considering the qualitative variable "Group". An initial analysis was made for all students in both institutions. Then, the same analysis is done for each establishment separately.

5.2.2 Student T-test

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

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

6 Results and interpretations

We will present the results obtained and their interpretations. Firstly, we conducted an ANOVA1 analysis to compare the three groups across the two institutes, and then we did it separately for each institute. At the end, by using the Student T-test, we make a comparison between the two institutes.

We based ourselves on the formulation of the null hypothesis. It is a question of globally testing the equality of the averages of the three groups.

- H_0 : there is no significant difference between the three groups.
- H_1 : at least one group is different from the others.

In an ANOVA1 analysis, and to compare between groups, the Tukey test is used. This proposes a significance threshold (Tukey significant difference called sig) of 5% (0.05). If the significance level obtained is less than 5%, then the null hypothesis H_0 is rejected and the hypothesis H_1 is retained, ie at least one group is different from the others.

6.1 ANOVA1 for the two institutes (public and private)

6.1.1 Analysis of the Precision variable

Using the SPSS software, the intergroup analysis of the Precision variable for the two grouped institutes gave a significance level (sig) of 0.000, which leads us to conclude that the Precision indicator is on average not identical in all three

groups. The null hypothesis H_0 is therefore rejected. The hypothesis H_1 is then retained, and it was necessary to know the group or groups that is or are different, making a multiple comparison of means.

6.1.2 Multiple comparisons of means

When the analysis of variance test is significant, we must conclude that there are significant differences between some of the averages of these normal populations. In this case, the multiple comparisons of means seek to determine a ranking of the means by indicating the significant differences and those that are not.

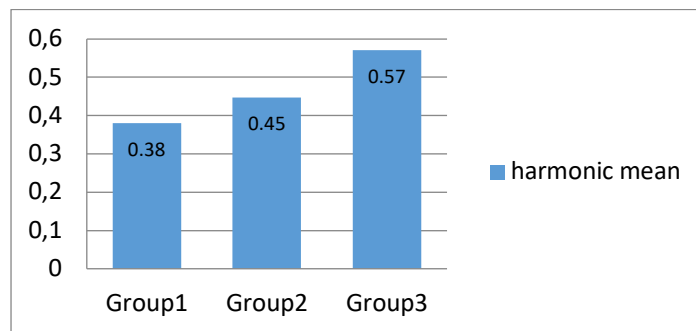
Table 7. ANOVA1-test on precision variable - the two institutes combined

	Group1	Group2	Group3
Group1		0.127	0.000
Group2	0.127		0.001
Group3	0.000	0.001	

According to the table of multiple comparisons and the Tukey method, a significance below the threshold of 0.05 makes it possible to identify the groups that give different results; so the groups G1 and G3 allow different average of Precision (sig = 0.000). It is the same for groups G2 and G3 (sig = 0.001).

The following analysis classifies groups into subsets, to find those with similarities and those that stand out.

Figure 5. Comparison of harmonic means–Precision variable, the two institutes combined



The figure 5 shows that the group 3 has a harmonic average much greater than the others groups 1 and 2. A classification in homogeneous subsets was subsequently made. The analysis give a result that distinguishes 2 subsets, the first one composed of groups G1 and G2 for which there is no significant difference, and the second one composed of group G3 which has an average precision of 0.57 (Table 8).

Table 8. Distribution into homogeneous subsets - Precision variable, the two institutes combined

	Size	Subset 1	Subset 2
Group1	26	0.38	
Group2	28	0.45	
Group3	28		0.57

It is therefore concluded that for the precision indicator, group G3 differs from the other two groups.

For the analysis of the other variables Recall and F-measure, we will see the same thing, so there is the same interpretation as for the case of the variable Precision.

6.1.3 Analysis of the Recall variable

The intergroup analysis of the Recall variable in the case of the two grouped institutes gave a significance level (sig) of 0.000 as well, which leads us to conclude that the Recall indicator is on average not identical in the three groups. The null hypothesis H_0 is then rejected and the hypothesis H_1 is retained. A multiple comparison must then be performed to determine the group or groups that stand out.

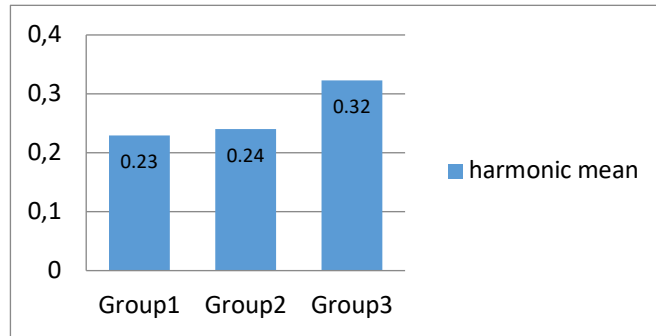
Table 9. ANOVA1-test on Recall variable - the two institutes combined

	Group1	Group2	Group3
Group1		0,830	0.000
Group2	0,830		0.000
Group3	0.000	0.000	

Table 9 shows a different average value of the Recall variable between group 1 and 3 (sig = 0.000), and also between groups 2 and 3 (sig = 0.000).

Comparison of harmonic means again gives a distinction for group 3 (figure 6) with an average of 0.32.

Figure 6. Comparison of harmonic means–Recall variable, the two institutes combined



The classification into homogeneous subsets gives a grouping of groups 1 and 2 in the same subset and group 3 in another (table 10).

Table 10. Distribution into homogeneous subsets - Recall variable, the two institutes combined

	Size	Subset 1	Subset 2
Group1	26	0.23	
Group2	28	0.24	
Group3	28		0.32

We therefore conclude that for the Recall indicator, group 3 is also different from the other two groups 1 and 2.

6.1.4 Analysis of the F-measure variable

For the F-measure variable, we have the same observation: the null hypothesis is rejected and the 3 groups therefore have a difference (sig = 0.000).

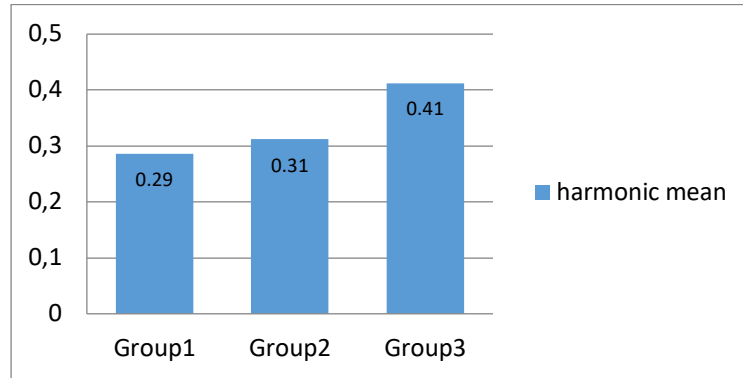
The multiple comparison of means again shows that the F-measure variable has a difference between group 1 and 3 (sig = 0.000) and also between group 2 and 3 (sig = 0.000) (table 11).

Table 11. ANOVA1-test on F-measure variable - the two institutes combined

	Group1	Group2	Group3
Group1		0,529	0.000
Group2	0,529		0.000
Group3	0.000	0.000	

The harmonic average comparison graph shows that group 3 always stands out with an average of 0.41 (figure 7).

Figure 7. Comparison of harmonic means – F-measure variable, the two institutes combined



And finally, the homogeneous subset classification always puts groups 1 and 2 in a homogeneous subset and group 3 in another (table 12).

Table 12. Distribution into homogeneous subsets - F-measure variable, the two institutes combined

	Size	Subset 1	Subset 2
Group1	26	0.29	
Group2	28	0.31	
Group3	28		0.41

We conclude that for variable F-measure, group 3 always stands out.

6.2 ANOVA1 for the public institute

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

In the case of the public institute, the inter-group analysis of the three Precision, Recall and F-measurement indicators gave a significance level equal to 0,000 each time, so the null hypothesis had to be rejected, and it was necessary to determine the group that stands out.

Table 13. ANOVA1-test on Precision variable – Public institute

	Group1	Group2	Group3
Group1		0.330	0.000
Group2	0.330		0.001
Group3	0.000	0.001	

Table 14. ANOVA1-test on Recall variable– Public institute

	Group1	Group2	Group3
Group1		0.990	0.000
Group2	0.990		0.000
Group3	0.000	0.000	

Table 15. ANOVA1-test on F-measure variable– Public institute

	Group1	Group2	Group3
Group1		0.904	0.000
Group2	0.904		0.000
Group3	0.000	0.000	

For the 3 variables, group 3 has a different mean value with respect to the other two groups 1 and 2 (tables 13, 14, 15).

The comparison of harmonic means also gives a distinction for group 3 with an average of 0.60 for the Precision variable, 0.34 for the Recall variable and 0.43 for the F-measure variable (figures 8, 9, 10).

Figure 8. Comparison of harmonic means – Precision variable, public institute

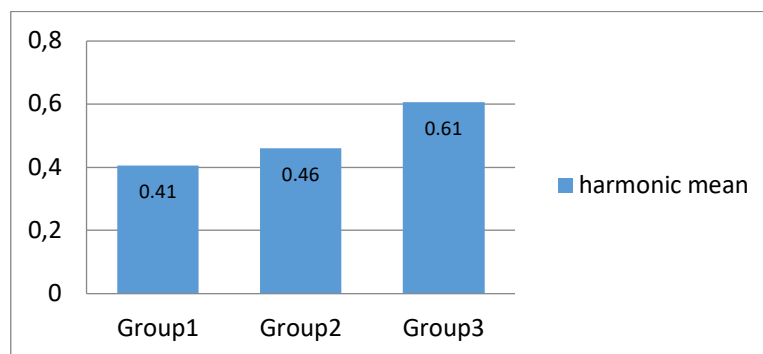


Figure 9. Comparison of harmonic means – Recall variable, public institute

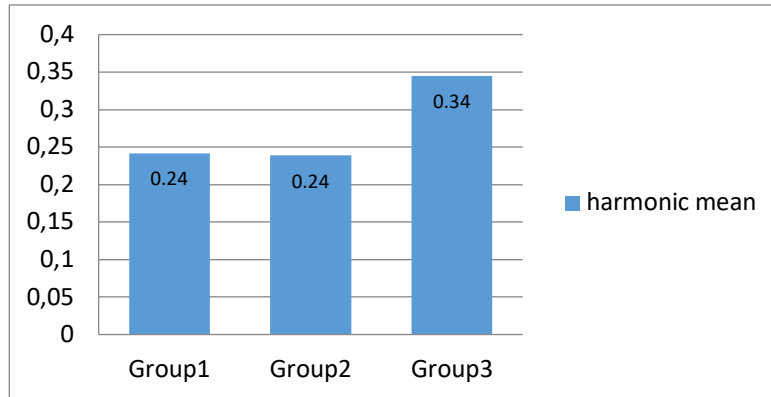
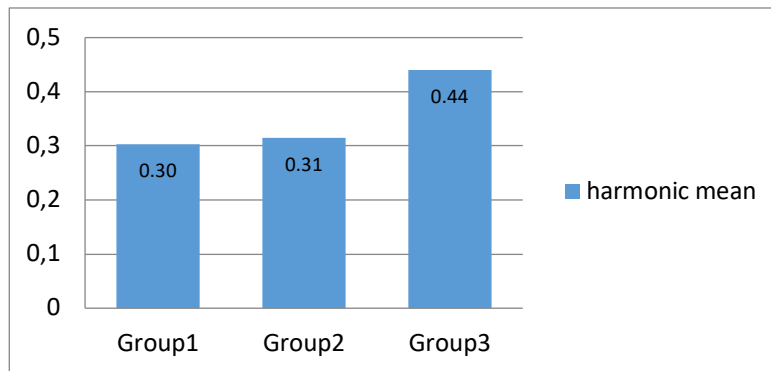


Figure 10. Comparison of harmonic means – F-measure variable, public institute



And with respect to the classification into homogeneous subsets, the analysis always gives the group 3 in one subset and the two groups 1 and 2 in another (tables 16, 17, 18).

Table 16. Distribution into homogeneous subsets - Precision variable, public institute

	Size	Subset 1	Subset 2
Group1	19	0.41	
Group2	21	0.46	
Group3	21		0.61

Table 17. Distribution into homogeneous subsets - Recall variable, public institute

	Size	Subset 1	Subset 2
Group1	19	0.24	
Group2	21	0.24	
Group3	21		0.35

Table 18. Distribution into homogeneous subsets - F-measure variable, public institute

	Size	Subset 1	Subset 2
Group1	19	0.30	
Group2	21	0.31	
Group3	21		0.44

We conclude that for the three Precision, Recall and F-measure indicators, group 3 is distinguished each time from the other two groups 1 and 2.

6.3 ANOVA1 for the private institute

For the private establishment, the ANOVA1 analysis showed a significant difference greater than the 5% threshold (0.68, 0.246, 0.161 respectively for the Precision, Recall and F-measure variables). This means that the hypothesis H_0 is retained and that the 3 groups do not show any difference. This is confirmed by the multiple comparisons. The homogeneous subset distribution also put the three groups in a same subset (tables 19, 20, 21).

Table 19. Distribution into homogeneous subsets - Precision variable, public institute

	Size	Subset 1
Group1	7	0.31
Group2	7	0.41
Group3	7	0.47

Table 20. Distribution into homogeneous subsets - Recall variable, public institute

	Size	Subset 1
Group1	7	0.19
Group2	7	0.24
Group3	7	0.26

Table 21. Distribution into homogeneous subsets - F-measure variable, public institute

	Size	Subset 1
Group1	7	0.24
Group2	7	0.31
Group3	7	0.33

We then find that for the private institute, there is no difference between the groups. This may be due to the reduced size of the three groups.

6.4 Student T-test between the two institutes

As we have already presented before, to consider the qualitative variable "Institute" and compare between the two private and public institutes, we used Student's T-test which is used to compare between two populations. The results are presented in the following.

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 is H_0 , there is no difference between public and private institute.

Tableau 22. Student T-Test for Precision, Recall and F-measure indicators

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

According to the results provided by the SPSS software, we note that for all three indicators the significance probability (sig) is below the 5% threshold (table 22), which leads us to reject the null hypothesis and conclude that for the three indicators there is a difference between the two institutes.

Table 23. Group statistics

Institute	Size	Average	Standard deviation	Mean standard error	
Precision	Private institute	21	0.40	0.13	0.03
	Public institute	61	0.50	0.14	0.02
Recall	Private institute	21	0.23	0.07	0.02
	Public institute	61	0.28	0.08	0.01
F-measure	Private institute	21	0.29	0.09	0.02
	Public institute	61	0.35	0.10	0.01

According to the table of group statistics (table 23), we can see that the values of the three indicators are higher, on average, among the students of the public institute. Especially the precision presents an interesting difference (0.49 compared to 0.39). Since the precision reflects the quality of the recommendations, we can explain this 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.

7 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 groups on both private and public institute, and by conducting an analysis of the impact of the qualitative variable "Group" on the three indicators, the group 3 clearly distinguishes itself from the other two groups 1 and 2. This confirms that the hybrid filtering approach conducted for group 3 gave better results for all three indicators.

The analysis was repeated on each institute separately. For public institute, we obtain the same result, that hybrid filtering provides more relevant recommendations. For 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 group 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, we find that the values of the three indicators are on average

higher among students at the public institution. It is especially the precision that presents a significant difference. Knowing that public institute students have often a higher level, we can assume that they are more relevant both in terms of resource sharing and in their appreciation (like).

8 Conclusion

In this article, we have described our experience in determining whether hybridization of two content-based filtering methods on the one hand and collaborative on the other can improve the relevance of recommendations in an online educational context.

The results showed that the hybrid recommendation approach works best when considering the public institution alone and when considering the public and private institutions together.

Several perspectives are planned in extension to this work; we plan to study the effect of the weighting of the two filtering approaches on the relevance of the recommendations. We can also consider an evaluation of resources on a scale of 1 to 5 instead of a binary evaluation (like or dislike), to have a more detailed appreciation. The inclusion of persuasion devices will also be an advantage to encourage participating learners to become more involved in the experience, such as obtaining badges after obtaining good third-party evaluation. We also plan to use the enriched database of learner profiles to provide external resources that match their preferences.

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