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QUALITATIVE RECOMMENDER SYSTEM USING ENTROPY-WEIGHTED PEDAGOGICAL CRITERIA FOR EFFECTIVE TRAINING IN E-LEARNING PLATFORMS

RAJAE ZRIAA[1], HICHAM SADIKI[2], MEROUANE ERTEL[3], SAID AMALI[4], NOUR-EDDINE EL FADDOULI[5]

[1,2,3]Informatics and Applications Laboratory (IA), Faculty of Sciences, Moulay Ismail University, Morocco

[4]Informatics and Applications Laboratory (IA), FSJES, Moulay Ismail University, Morocco
[5]RIME Team, MASI Laboratory, E3S Research center EMI, Mohammed V University, Morocco

E-mail: [1] r.zriaa@edu.umi.ac.ma, [2] h.sadqui@umi.ac.ma, [3] m.ertel@edu.umi.ac.ma,
[4] s_amali@yahoo.com, [5] noureddine.elfaddouli@um5.ac.ma

ABSTRACT

Recommender systems based on collaborative filtering have been widely used in many online learning systems, in order to help learners, find appropriate learning resources. However, these systems are based on classical similarity measures exploiting only learners' ratings for learning objects said subjective preferences, to form groups of learners with similar interests. This paper aims at exploiting also pedagogical criteria of the learning objects, in order to improve the classical similarity measures to generate qualitative recommendations. For this reason, we adopt a Shannon Entropy approach, combining heuristic weights with classical similarity measures, in order to produce recommendations evaluated by their subjective quality, and by their objective usefulness to support learners in their learning process.
Keywords: *Recommendation System; Machine Learning; Hybrid Filtering; Shannon Entropy; Pearson Correlation; E-Learning; Qualitative Recommender System.*

1. INTRODUCTION

Recently, e-learning platforms have experienced a massive expansion, however, with the growth of digital resources, access to the information desired by the learner in a timely manner is one of the marked problems in distance learning environments, as the learner needs relevant suggestions throughout their learning journey in order to achieve their goals in the best conditions [1]. To this end, a variety of information access methods have been proposed in the literature, in order to offer the learner a personalized space according to his preferences and needs [2].

while exploiting similarities between learners based on their experiences, behaviors, preferences and interests to formulate appropriate recommendations [5]. Each of these techniques suffer from certain weaknesses, in content-based filtering, the problem of serendipity is the most recognized; learners may receive the same

Recommender systems are promising new technologies in Human Learning Computing Environments (HLEs), as they can alleviate the problem of information overload [3][4], while highlighting what is most relevant and interesting according to the learner's profile.

Several filtering techniques have been widely used in recommender systems such as: content-based filtering (CBF) which exploits the characteristics of learning objects to generate recommendations, and collaborative filtering (CF) which takes advantage of learners' ratings for a resource to suggest appropriate learning objects,
recommendations, whose learning objects are similar to those they have already evaluated before, this redundancy generates the so-called Filter Bubble [6]. This increases the risk that learners have no chance to receive unexpected recommendations which leads to recommendation weariness. In addition,

collaborative filtering suffers from two major problems, namely: the cold start problem [7][8] which is caused by the lack of data on new items or new users. Indeed, a new item cannot be recommended until a user has evaluated it. Similarly, for a new user, we can't predict their preferences without knowing their item rating history. There is also the problem of sparsity [9] –[11], which occurs when the number of items rated by users is very small compared to the total number of items available in the system. Sparsity results in a very low density of the matrix (items/user). This has consequences on the ability of the system to recommend less accurate items. In this regard, hybrid filtering is one of the solutions considered to overcome the previous limitations. This technique aims at combining the strengths of the two recommendation techniques explained above, in order to benefit from their complementary advantages, moreover, several hybridization methods have been proposed by Burke [12] such as: weighting, switching, mixed, feature combination, cascading, feature augmentation and meta-level.

This paper presents a hybrid recommender system, supported by a new methodological approach that combines subjective preferences (learners' ratings) and objective preferences (LOs' pedagogical criteria).The entropy function and correlation coefficients are used as an underlying technique, to elicit the pedagogical criteria of the learning objects most valued by the learner, with the aim of improving the performance of the recommendations, thus providing an effective and efficient learning experience.

The rest of the paper is organized as follows. In section 2 we represent related research work, in section 3 we describe our proposed approach:

Hybrid model based on learners' subjective and objective preferences and in section 4 we conclude the paper and suggest possible future works.

2. RELATED WORKS

Research on recommender systems in the e-learning domain has seen significant interest, of which several works have been conducted on recommender systems in the online learning environment, such as: Monsalve-Pulido et al.[13] have proposed an architectural design of an intelligent and autonomous recommendation system to be applied to any virtual learning environment, in order to recommend digital resources; This architecture is based on hybrid model allows the integration of the approaches based on collaborative filtering, content-based filtering and knowledge. Esteban et al. [14] proposed a hybrid multi-criteria recommender system to suggest an appropriate course by combining a collaborative filtering model based on student profile including reviews and ratings assigned to courses, and a filtering model based on a domain model including professors and course content. Feng Zhang et al. [15] proposed a recommender system based on the collaborative filtering approach to recommend learning resources that are valued by learners most similar to the active learner. In 2018, Hayder Murad et al. [16] designed a recommender system that detects students' profiles and knowledge levels, with the aim of automatically recommending online video learning materials that are perfectly suited to students' needs. In 2017, Tarus et al. [17] proposed a hybrid ontology-based recommender system with sequential pattern mining to recommend online learning resources to learners. In 2015, Bokde et al. [18] develop an academic recommender system, which provides engineering school students with recommendations that meet their past preferences, based on a hybrid technique that combines article-based multi-criteria collaborative filtering with a dimensionality reduction approach. In addition, a tutoring system based on a recommendation engine Protus (ProgrammmingTUtorting System) [19] was designed to recommend materials of interest to learners, while taking into account their pedagogical differences such as: preferences, knowledge, learning goals and learner progress, etc. The initial recommendation in Portus is based on the default sequence of lessons and the surveys previously assigned to the lessons.

Recommendation approaches applied in e-learning are mainly based on learners' ratings of digital learning resources (DLRs). The filtering process used in these types of systems often starts with the idea that, the characteristics of the learning objects referred to as pedagogical criteria are of equal importance for all learners.

Most of the work done in the field of distance learning, that is based on content-based filtering (CB) or collaborative filtering (CF) doesn't link learners' ratings to the pedagogical criteria of the learning objects.Yet, in reality, in order to

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benefit from effective learning within e-learning platforms, recommendations must rely more on the pedagogical criteria of the learning objects, to improve the learning process. For this purpose, pedagogical criteria must be incorporated, in particular, in the recommendation process, so that learners' ratings for a learning object become more meaningful, in parallel the recommendations are more explanatory, transparent and qualitative.

Thus, the main objective of this contribution is to design a hybrid recommendation model (CBF and CF), which combines explicit learner ratings and pedagogical criteria of learning objects in the recommendation process. This approach allows on the one hand, to clearly elicit the learners' interests towards the learning objects and on the other hand, to benefit from more interesting and relevant recommendations.

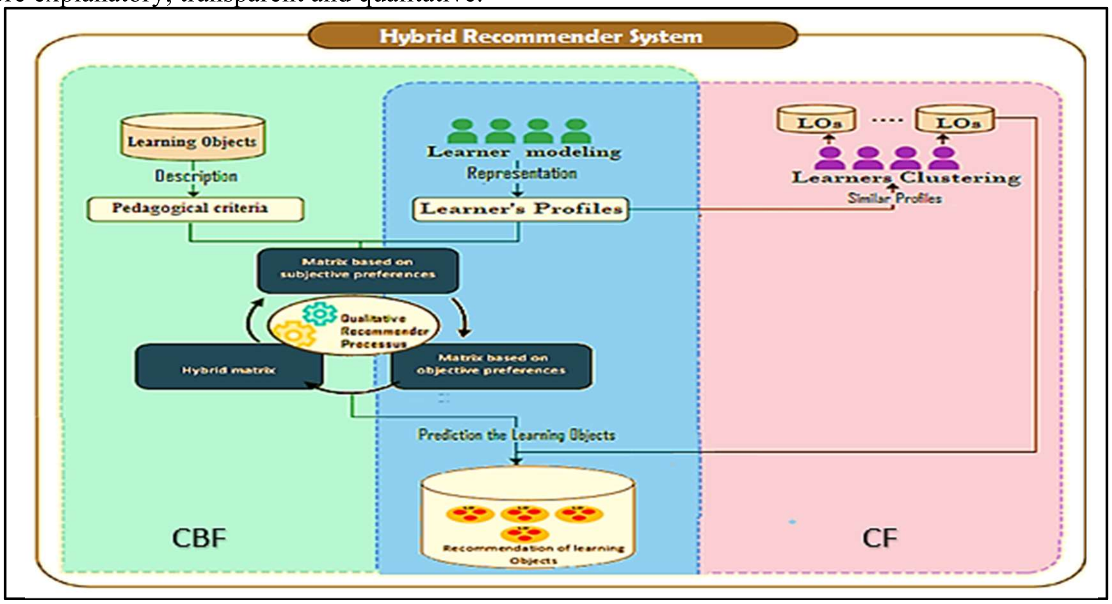

Fig.1 Hybrid Recommender Model

3. PROPOSED MODEL

The proposed model (Cf. Figure 1) illustrates our hybrid recommendation system, which is based on learners' ratings for learning objects (subjective preferences), and pedagogical criteria of learning objects (objective preferences) in e-learning; In order to build a hybrid matrix, that represents the set of learning objects with their pedagogical criteria weighted according to the learners' ratings. After building a domain model, which describes the set of learning objects with their pedagogical criteria defined by the course designers in the e-learning platform, and a learner model which is based on the PAPI (Public And Private Information for Learner) [20].

This standard was developed by (IEEE P1484 Learner Model Working Group), to model the learner in the learning system through the various information specified in the learner's profile, namely: personal or demographic information, relational information, information on preferences, information on the learner's history and progress in learning. A clustering approach is then used to classify learners into virtual communities of similar interest, to easily predict the future preferences of each learner.

In this paper, we focus more on the qualitative recommendation process of our hybrid system which takes place in three steps as illustrated in Figure 2.

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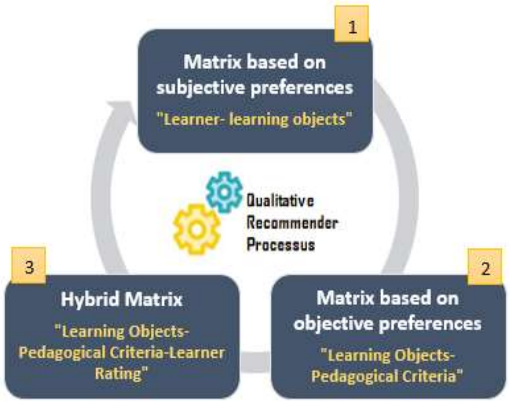

Fig.2 Qualitative recommendation process

In the first step, a matrix based on subjective preferences is built containing all the ratings given by the learners for the learning objects, then a matrix based on objective preferences including the learning objects with their pedagogical criteria such as: the duration of the support, the level of difficulty of the resource, the level of the objective according to the taxonomy of BLOOM, and the learning support. A hybrid matrix established by a weighting approach of the pedagogical criteria, according to the learners' ratings, while being based on Shannon's entropy method and the correlation coefficients.

3.1 Research Methodology

In this phase, we explain the different steps followed to identify the learners' preferences not only on the basis of the ratings approved by them, but also according to the pedagogical criteria associated with the learning objects, with the aim of building hybrid recommendations based on the objective and subjective preferences of the learner.

3.1.1 The subjective preferences

The explicit behaviors of the learners within the system are represented in a matrix, that indicates the set of ratings attributed by the learners during their interactions with the learning objects, these ratings are represented on a 5-point Likert-type scale, ranging from 1 "Don’t like" to 5 "Very like" as shown in Table 1.

Table 1. Instrument and resources

Linking	Rating scale
Very like	5
Like	4
Neutral	3
Not like	2
Do not like	1

3.1.1.1 Learner-Learning Object Matrix

After the evaluation phase of the learning objects, a learner learning object matrix is established to represent the learner's subjective preferences (Cf Figure 3).

	lo_1	lo_2	lo_3	lo_4	..	..	lo_m
l_1	r^1_1	r^1_2	r^1_3	r^1_4	..	..	r^1_m
l_2	r^2_1	r^2_2	r^2_3	r^2_4	..	..	r^2_m
l_3	r^3_1	r^3_2	r^3_3	r^3_4	..	..	r^3_m
l_4	r^4_1	r^4_2	r^4_3	r^4_4	..	..	r^4_m
..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..
l_n	r^n_1	r^n_2	r^n_3	r^n_4			r^n_m

Fig.3 Matrix "Learner-Learning Objects"

For each learner l_i, it exists in its profile the set of learning objects $LO_{li}=\{lo^{li}_j \in LO, j=1\ldots_i\}$, where lo^{li}_j the learning object j consulted by the learner ‘l_i’, the learner's ratings for a learning object are described by r^{li}_j.

3.1.2 The objective preferences

3.1.2.1 Pedagogical Criteria for Learning Objects

Learning objects (LOs), as defined by the Institute of Electrical and Electronics Engineers (IEEE) Learning Technology Standards Committee, "are any entity, digital or non-digital, that can be used, reused, or referenced during technology-enhanced learning" (IEEE, 2002). This definition includes any form of learning material that can be used during "technology-enhanced learning." In addition, in the context of e-learning, learning objects are defined as "any entity, digital or otherwise, that can be used, reused or referenced during technology-supported learning.

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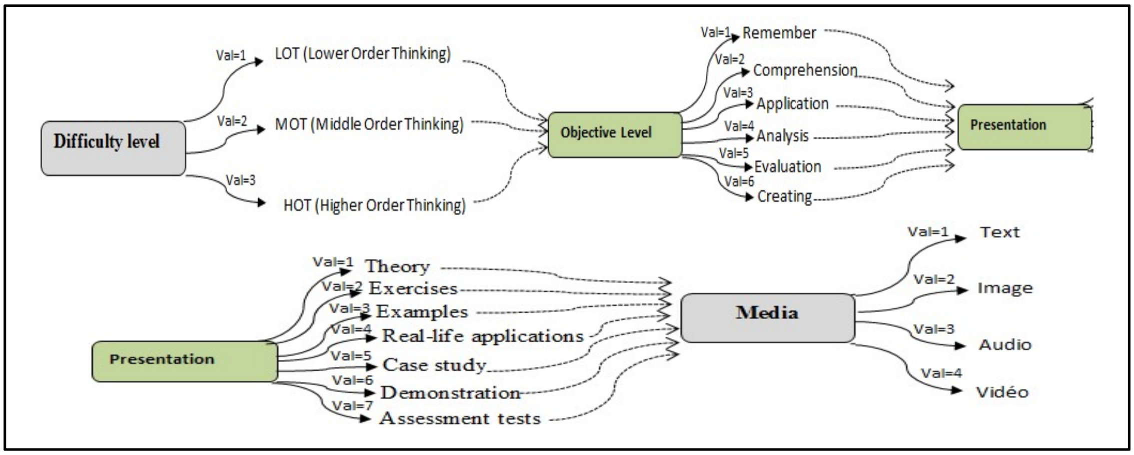

Fig.4 Pedagogical Criteria of Learning Object

Examples of technology-supported learning include computer-based training systems, interactive learning environments, intelligent computer-based teaching systems, distance learning systems, and collaborative learning environments. Examples of learning objects include multimedia content, instructional content, learning objectives, instructional software, and software tools, as well as the people, organizations, or events to which technology-enhanced learning refers."[21].

Furthermore, the customization of e-learning environments should not only be based on the descriptive metadata of the learning objects, but it should also take into consideration the pedagogical criteria associated with the learning objects. These criteria play a very important role in the classification and description of learning objects from a pedagogical point of view, this description concerns the content, the presentation and the media whose values are multiple and heterogeneous (Cf Figure 4).

3.1.2.2 Learning object-pedagogical criteria Matrix

The domain model describes the various hierarchies used in the learning process including the relationships between the learning objects in the e-learning platform. These objects are stored in a directory containing a set of alternatives {Alternative i, i=1…m} characterized by criteria $\{c_j , j = 1...p\}$ defined by the designers of the learning units and which are part of a specific domain D_j. Each Learning Object lo_i is represented by a vector $V_i= \{v_{ij} \in D_{j,j}=1\ldots p\}$ describing the pedagogical criteria (Cf Figure 5).

	c_1	c_2	c_3	c_4	..	..	c_p
lo_1	v^1_1	v^1_2	v^1_3	v^1_4	..	..	v^1_p
lo_2	v^2_1	v^2_2	v^2_3	v^2_4	..	..	v^2_p
lo_3	v^3_1	v^3_2	v^3_3	v^3_4	..	..	v^3_p
lo_4	v^4_1	v^4_2	v^4_3	v^4_4	..	..	v^4_p
..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..
lo_m	v^m_1	v^m_2	v^m_3	v^m_4			v^m_p

Fig 5. Matrix « Learning object-pedagogical criteria»

3.1.2.3 Matrix "Learning Objects-Pedagogical Criteria-Learner Rating"

The construction of the hybrid matrix (Cf Figure 6) is done, through the conjunction of the two matrices mentioned above. In this regard, we have proposed an approach to weighting the pedagogical criteria according to the ratings, based on the entropy method and the Pearson correlation coefficient.

	c_1	c_2	c_3	..	..	c_p	r_{cl}
lo_1	v^1_1	v^1_2	v^1_3			v^1_p	r^{cl}_1
lo_2	v^2_1	v^2_2	v^2_3			v^2_p	r^{cl}_2
lo_3	v^3_1	v^3_2	v^3_3			v^3_p	r^{cl}_3
lo_4	v^4_1	v^4_2	v^4_3			v^4_p	r^{cl}_4
..	..	..	..			..	..
..	..	..	..			..	..
lo_m	v^m_1	v^m_2	v^m_3			v^m_p	r^{cl}_m

Fig 6. Matrix « Learning Objects-Pedagogical criteria-ratings for each learner»

For each learner cl, , it exists in its profile the set of learning objects $LO_{cl}=\{lo^{cl}_i \in LO, i=1\ldots m_{cl}\}$,

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where lo^{cl}_i are the learning objects consulted by the current learner 'cl', the values of the pedagogical criteria are described by v^{cl}_i ,the values of the pedagogical criteria are described by r^{cl}_i .

3.1.3 Entropy-weighted pedagogical criteria

Manuel Jose Barranco proposed a technique of weighting the features and which is articulated in three steps [23], as illustrated in Figure 7:
Step 1: *Compute the inter-user similarity*
In this phase, we proceed to the use of the entropy function Hj, which allows to identify which features are more relevant for the user.
Step 2*: Compute the intra-user similarity*
During this step, the correlation between the elements already evaluated in the user's profile, and the values of the characteristics on the set of elements is calculated; when these characteristics are quantitative values, otherwise the contingency is used in case the values are qualitative.
Step 3: *Feature weight calculation*
The weight of the feature is calculated while using the results provided by the entropy function (step1) and the degree of dependency (step 2).

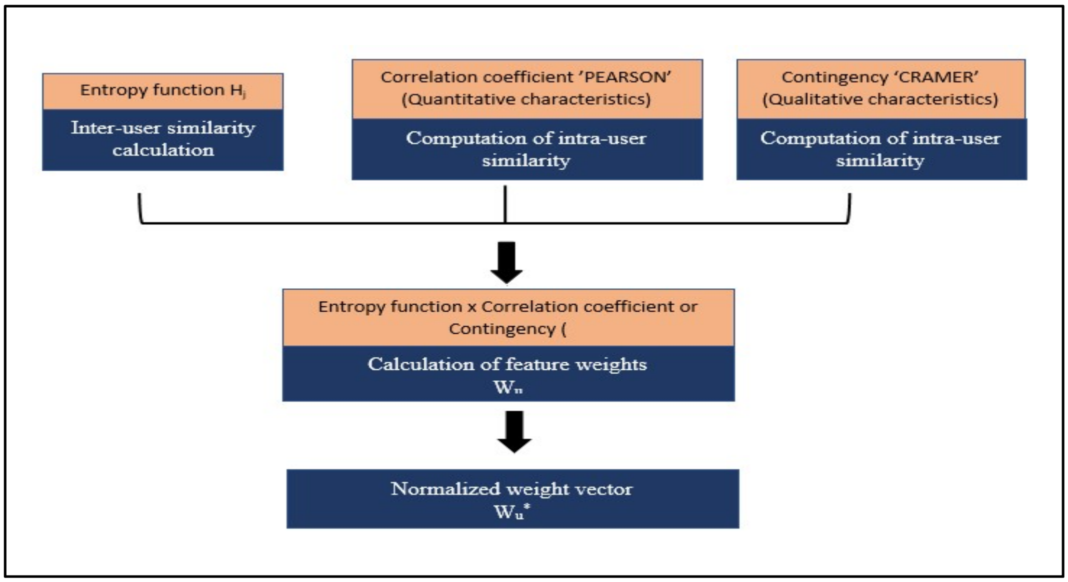

Fig.7 Weighting of the characteristics on the basis of the entropy and the degree of dependence

3.1.3.1 Shannon's entropy method

In 1948, Claude Shannon developed the general concept of entropy and information, this formula of Shannon is part of the theories of physics and it isomorphic to the formula of entropy of Boltzmann. This theory is used in scientific fields (thermodynamics with the entropy theory, physics with the signal concepts, infometrics with the statistical concepts...) [24][25]. Moreover, the entropy method plays a primary role in the study of uncertainty in a system, for this reason it is called "information entropy". Later works underline that the Shannon entropy allows the resolution of problems in decision science [26][27]. In particular, to determine the weight of a criterion or attribute.

In our research framework, we are interested in the probabilistic theory of information called "Information Entropy" or sometimes called "Shannon Entropy", which is globally articulated on the quantitative study of information while formulating a track of the key ideas of the theory of information, and it refers to a set of techniques of mathematical and statistical measurements of information. Our ultimate goal is to study the diversity of information, particularly that related to the description of the content of the learning objects, in order to highlight the importance of the pedagogical criteria according to the evaluations attributed by the learners (Cf Figure 8).

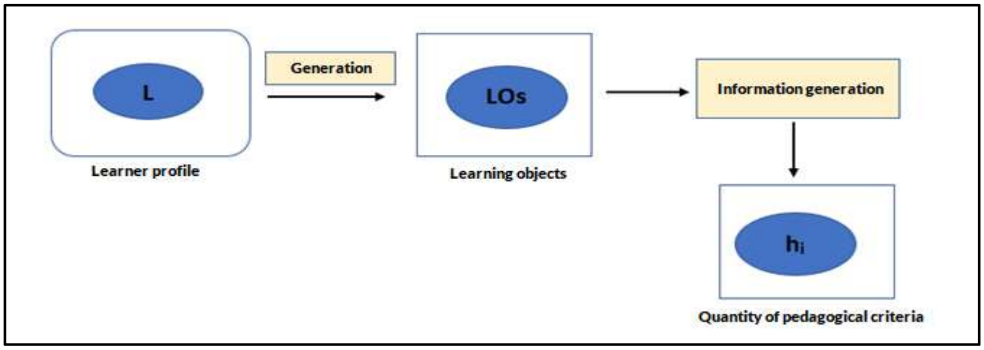

Fig.8 Process for extracting pedagogical criteria and the degree of dependence

In addition, Shannon's entropy method allows to determine the importance of criteria or characteristics, through their values while taking into account the distribution of these values; where the characteristic with a more uniform distribution obtains a higher entropy value.
In other words, the entropy allows in a standard way to quantify the average information contained in an observation, and it allows to measure the discrimination or the dispersion of values.
Shannon [28] defined entropy in terms of a discrete random variable X, with possible states or outcomes n whose probabilities of occurrence are $x_1,x_2,x_3,\ldots\ldots.x_n$. (1)

$$H(X) = -\sum_{i=1}^{n} p(x_i)\, log_2 p(x_i) \quad (1)$$

Where:
$p(x_i)$= Probability ($X=x_i$): is the probability of i[ème] result of X ; is the frequency of occurrence of the value of an attribute f_{vj} compared to the number of variables m.

$$Hj = -\sum_{vj}^{m}\left(\frac{f_{vj}}{m}\right) log_2\left(\frac{f_{vj}}{m}\right) \qquad (2)$$

$0 \le H(X) \le 1$: the entropy function H(X) is between 0 and 1 ; the normalization of the entropy is done through the following equation (3) :

$$H^*{}_j = \frac{H_j}{\sum_{j=1}^{p} H_j} \qquad (3)$$

3.1.3.2 Classification of pedagogical criteria in terms of entropy (low, medium, high)

The classification of pedagogical criteria allows us to determine the weight or importance of pedagogical criteria for all learning objects, based on the ratings assigned by each learner, in order to elicit the objective preferences of each learner and to find the most similar learners based on these objective preferences.
If **H(X) = 0**: low entropy; designates that the values of pedagogical criteria for all learning objects are similar; strong knowledge of objective learner preferences.
If **0<H(X)<1**: average entropy; refers to the values of the pedagogical criteria being almost similar, i.e., there are a few different values; An average knowledge of objective learner preferences.
If **H(X) =1**: high entropy; means that the values are totally different; low knowledge of the learner's objective preferences.

3.1.3.3 Weighting of pedagogical criteria based on learner rating

Following the steps proposed by Manuel Jose Barranco to calculate the weights of the attributes, we have adapted this approach in the framework of e-learning through the following phases:
Step *1: Computes the inter-learner similarity*
In this step, we proceed to the calculation of the entropy of each pedagogical criteria, for the set of learning objects marked in the learner's profile. For this, the combination of the two matrices $M1[l_n, lo_m]$ et $M2[lo_m ,c_p]$ is necessary, in order to generate a multidimensional matrix $M3[lo_m ,c_p,r_m]$, which includes three elements : learning objects, pedagogical criteria and ratings assigned by the learner (Cf Figure 9).

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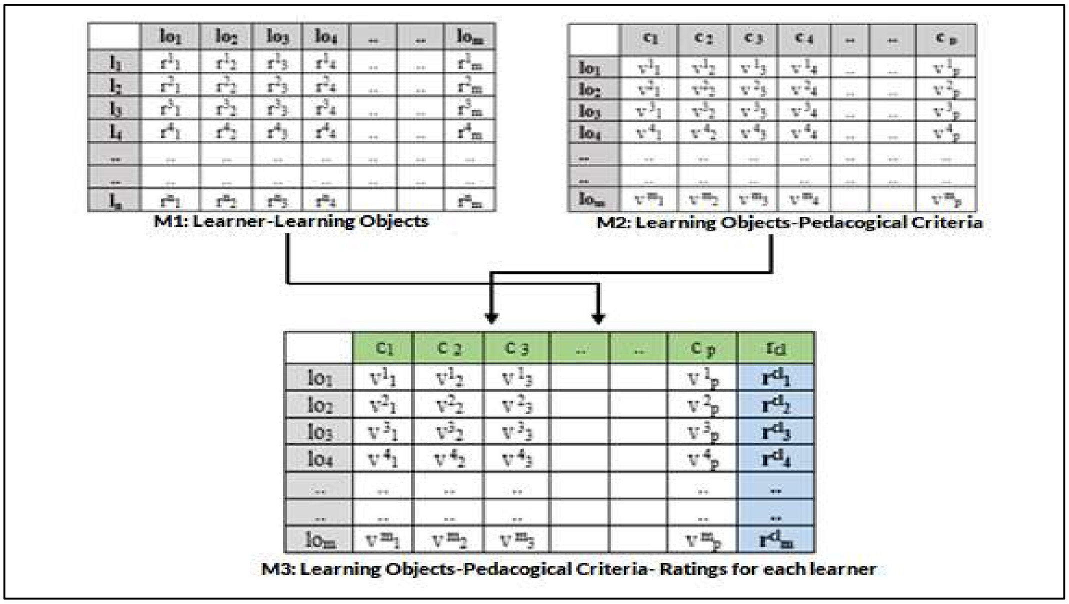

Fig.9 Hybridization between subjective and objective preferences

Step 2: *Computation of the intra-learner similarity*
Multi-attribute decision making (MADM *multi-attribute decision-making*) is to extrapolate the actual preferences of the learners, these preferences are weighted by the subjective and objective preferences [29]; For this purpose, we calculate the dependency coefficient (DC) between the pedagogical criteria and the ratings attributed by the learner to the learning objects.
Several measures of dependence are considered depending on the nature of the characteristics; for quantitative data we use the correlation coefficient such as: Pearson Correlation Coefficient, Spearman Rank Correlation, ...etc. and for qualitative data we rely on the contingency coefficient, e.g. Cramer's V coefficient [30].
In our context, the correlation coefficient is used instead of the contingency coefficient; because the pedagogical criteria are expressed as quantitative values.
The Pearson correlation coefficient is used to measure the degree of association of two variables and the strength of a linear relationship between matched data. This coefficient is used when the data are linearly related and approximately or normally distributed; otherwise, the use of the Spearman Rank Correlation measure is necessary when the variables used are represented in a more or less ordinal scale.

PradeepKumar Singh and his collaborators [31] have focused on correlation measures such as: Pearson correlation and Spearman Rank correlation in collaborative recommender systems, from the results experienced by their experimentation, it is found that Person correlation performs the best compared to other similarity measures such as Spearman Rank.
The dependency coefficient (DC): is calculated through the Pearson correlation coefficient in order to identify the degree of association between the ratings provided by the learner 'cl' for all the learning objects 'LOm' consulted and the quantitative values of the pedagogical criteria 'Cp'.
Pearson Correlation Coefficient (PCC)[32]: is a statistical measure of the linear relationship between two variables and ranges from [-1,+1]. Positive correlation indicates that the variables are increasing or decreasing in parallel, however, negative correlation means that one variable is increasing while the other is decreasing (Cf Figure 10).

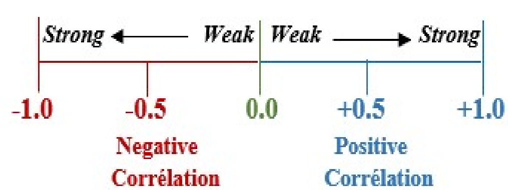

Fig.10 Correlation coefficient: Shows strength and Direction of correlation

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In addition, correlation [33] is an effect measure where the strength of the correlation is described as follows (Cf Table 2), with ***-1.0≤ r ≤+1.0*** :

Table 2: the r value and their interpretation

r value	Interpretation
+.80 to +1.0	Very strong positive relationship
+.60 to +.79	Strong positive relationship
+.40 to +.59	Moderate positive relationship
+.20 to +.39	Weak positive relationship
+.01 to+.19	Negligible relationship
0	No relationship
-.01 to -.19	Negligible relationship
-.20 to -.39	Weak negative relationship
-.40 to -.59	Moderate negative relationship
-.60 to -.79	Strong negative relationship
-.80 to -1.0	Very strong negative relationship

The correlation value 'r' is calculated as shown in equation (4):

$$r_{x,y} = \frac{\delta xy}{\delta x \, \delta y} \quad (4)$$

where:

$$\delta xy = \frac{1}{n}\sum_{i=1}^{n} x_i y_i + \bar{x}\bar{y} \quad (4.1)$$

$$\delta x = \sqrt{\sum_{i=1}^{n} \frac{x_i^2}{n} - \bar{x}^2} \quad (4.2)$$

$$\delta y = \sqrt{\sum_{i=1}^{n} \frac{y_i^2}{n} - \bar{y}^2} \quad (4.3)$$

Based on the formula (5) proposed by Manuel J. Barranco and Luis Martinez, Pearson's correlation coefficient is associated with two variables: the pedagogical criteria of the learning objects and their ratings by the learners.

$$PCC_{\ cl\ j} = \frac{\sum_i r_i^{cl} v_{ij}^{cl} - \frac{\sum_i r_i^{cl} \sum_i v_{ij}^{cl}}{n_{cl}}}{\sqrt{\left(\sum_i (r_i^{cl})^2 - \frac{\left(\sum_i r_i^{cl}\right)^2}{n_{cl}}\right)} \sqrt{\left(\sum_i \left(v_{ij}^{cl}\right)^2 - \frac{\left(\sum_i v_{ij}^{cl}\right)^2}{n_{cl}}\right)}} \quad (5)$$

Where:

r_i^{cl}: Score assigned by the learner 'cl' for the learning object 'lo_i'.

v_{ij}^{cl}: Pedagogical criteria 'v_j' for the learning object 'lo_i' consulted by the learner 'cl'

n_{cl}: Number of learning objects consulted by the current learner 'cl' .

Step 3: *Calculation of the weight of the pedagogical criteria of the LOs (Degree of preference of the LOs)*

The weight of the PCs (pedagogical criteria) is calculated on the basis of the results provided by the entropy function (step 1) and the degree of dependence (step 2). The weight of each pedagogical criteria for each learner is calculated through formula (6) (Cf Figure 11).

$$W_j^{cl} = H^* \ x \ |PCC|_{cl\ j} \quad (6)$$

	c_1	c_2	c_3	..	..	c_p
lo_1	v^1_1	v^1_2	v^1_3	..	..	v^1_p
lo_2	v^2_1	v^2_2	v^2_3	..	..	v^2_p
lo_3	v^3_1	v^3_2	v^3_3	..	..	v^3_p
lo_4	v^4_1	v^4_2	v^4_3	..	..	v^4_p
..	..	..	..	..	..	..
..	..	..	..	..	..	..
w_1	w_1	w_2	w_3	..	..	w_p

Fig.11 Weighted matrix based on the entropy and the degree of dependence

Where:

Alternatives: are the possible learning objects m and they are represented by LO = {lo_i |i ∈ M}, where M={1,2,…,m}

Attributes or criteria: are the set of pedagogical criteria that describe the pedagogical characteristics of the learning objects, and they are represented as follows C= {cj|j∈ P} where P ={1, 2, . . ., P}

Weight or importance of criteria: is the vector weight of the pedagogical criteria for all the learning objects evaluated by the learner w = (w_1,. . ., w_j,. . ., w_p), with $0 \le w_j \le 1$.

4. RESULT AND FINDING

This section presents an analysis of the performance of the proposed methodology. The performance of this work is evaluated against the recommendation based only on the subjective preferences of the learners.

The participants in this experiment are 40 students from a high school in the delegation of Tetouan, Morocco. However, the students had to study four modules in the computer science subject, namely: "Generalities of computer systems", "Software", "Algorithms and programming" and "Networks and Internet"; each module consists of a set of lessons, which are well defined in the pedagogical guidelines of computer science in high school.

Our first experiment is based on the first module "Generalities of computer systems", which contains three lessons: lesson 1 "Basic

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definitions and vocabulary", lesson 2 "Basic structure of a computer" and lesson 3 "Software and application domains of computer science"; each lesson is associated with a set of learning objects of different types Texts, Images, videos ,etc. (Cf Table 3).

Table 3. Module N°1 "Generalities on computer systems"

		Common Core			
Content	Schedule	Letter & Arts	Original	Science	Technologies
Definition and basic Vocabulary	2h				
Definition of information		2	2	2	2
Definition of treatment		2	2	2	2
Definition of computer Science		2	2	2	2
Definition of the computer system		2	2	2	2
Basic structure of a computer	4h				
Functional diagram of a Computer		2	2	3	3
Peripherals		2	2	3	3
Central processing unit		2	2	3	3
Types of software	1h				
Basic software		2	2	2	2
Application software		2	2	2	2
Fields of application	1h	2	2	2	2

The table 4 illustrates the depth of the learning objects for each concept.

Table 4. The degree of depth

Degree of depth	Descriptor
1	Initiation
2	Appropriation
3	Master

Our approach is tested on learning objects stored in the LMS database. The first module "General Computer Systems" provides an assessment dataset of 50 learning objects containing 36 ratings from 26 learners. The ratings are integers ranging from 1 to 5, The experiments are performed on an HP computer with CORE i5 processors.

4.1 Comparative study between simple entropy and weighted entropy:

The proposed recommendation system generates in its cache a matrix (Cf Figure 12), that represents the subjective and objective preferences of the current learner, where each pedagogical criteria is identified by a weight, in order to make the recommendations more qualitative and the learning more meaningful.

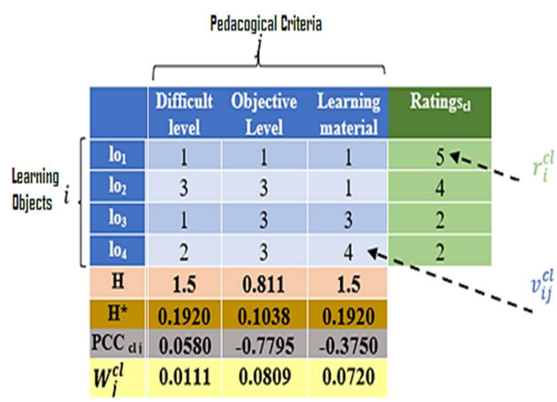

Fig. 12 Weighted matrix of a current learner(cl)

From the results shown in the matrix above, we can see that Shannon's entropy method (H*) isn't only limited to the discriminating aspect of the features, that is to say that the criteria having more or multiple values are more discriminating than those having less values, but it also takes into account the distribution of these values; that is to say that the features having a more uniform distribution receive a higher entropy value.

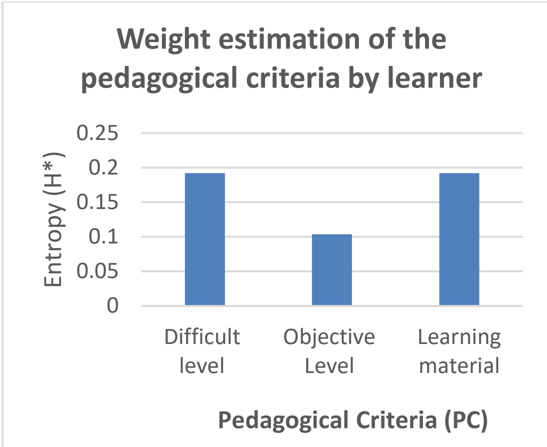

Fig.13 Simple Shannon Entropy of pedagogical criteria

Moreover, limiting oneself to the simple measure of entropy to estimate the objective weights of the pedagogical criteria can generate some confusion, in order to identify the most dominant and frequent pedagogical criteria in the learner's learning process, as illustrated in Figure 13. Some criteria may have the same appearance weight, such as the case of the couple {Learning material, Difficult level} which makes the preference elicitation task more complex and less accurate. For this reason, weighting the entropy function with the ratings assigned by the learner to the learning objects (subjective preferences) helps to strengthen the preference elicitation process, and increase the accuracy rate.

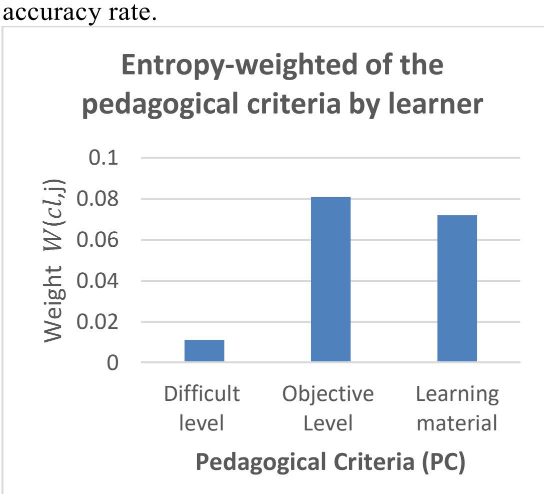

Fig.14 Entropy-weighted of pedagogical criteria

From the graph in Figure 14, we can see that when the value of the weight of the pedagogical criterion is high, it implies a strong knowledge about the objective preferences of the learner; for example, we take the case of the pedagogical criteria "Objective Level" whose weight value is 0. 0809; this value indicates that the learning objects most recommended to the learner are associated with the BLOOM taxonomy level "Application"; therefore, it means that the learner has a tendency towards application learning activities, that must be represented in the form of Real-life applications (Simulation) or case study.

4.2 Weighted entropy-based clustering performance

Clustering is used to build virtual communities of similar interest, while classifying learners with similar needs into groups. In this paper, we use the K-means algorithm to cluster learners based on the weighted matrix.
We can see from Figure 14, that in the clustering based on simple entropy, most of the learners are assigned to the same cluster (C4), this distribution is due to the low precision of the learners' preferences in terms of pedagogical criteria. This is explained by the insufficient data on the learner's profile, which leads to a loss of precision when assigning learners to clusters. However, the grouping of learners via clustering based on weighted entropy allows on the one hand, to well determine the inter-learner preferences and on the other hand, it allows to well assign learners in the right cluster whose needs are similar. Also, recommendations become more qualitative and meaningful in the e-learning system.

4.3 Measuring the effectiveness of the proposed model

The mean absolute error (MAE) (Equation 7) is a metric for measuring prediction quality and indicates the absolute value of the difference between the predicted value and the actual value. This metric is used to indicate the effectiveness of our weighted entropy-based recommendation system; the lower the MAE value, the smaller the magnitude of the error.

$$MAE = \frac{\sum_{(u,i)\in\, test} |prediction_{u,i} - real_{u,i}|}{n_{test}} \quad (7)$$

Where:
n is the total number of ratings-prediction pairs in the test set, $prediction_{u,i}$ is the predicted rating for learner u on learning object j, and $real_{u,i}$ is the actual rating in the real dataset.

Table 5. MAE according to the different types of clusters

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	Number of clusters	Clustering based on simple entropy	Clustering based on weighted entropy
MAE	K=2	0.12360	0.09656
	K=3	0.12749	0.05743
	K=4	0.09292	0.04106

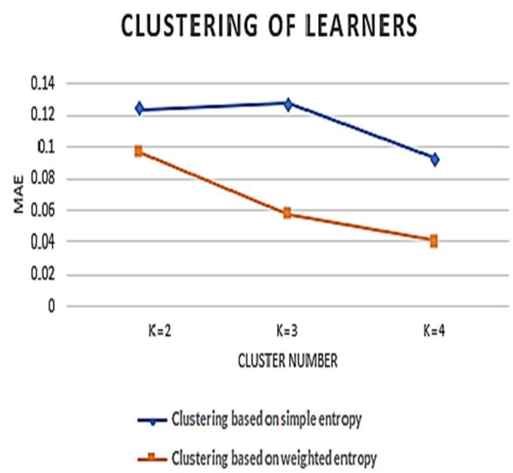

Fig.16 MAE according to clustering

We see from Figure 16, that the value of the average absolute error obtained as a function of the number of clusters is lower for the weighted entropy-based clustering, compared to that obtained in the simple entropy-based clustering. This is due to the elicitation of learners' preferences by weighting the learning object ratings with the associated pedagogical criteria. Thus, the prediction quality for our hybrid model is more accurate compared to the standard recommendation model (Cf Table 4).

The hybridization between objective preferences (the pedagogical criteria of the LOs) and subjective preferences (the learner's ratings) allows on the one hand, to precisely rank the pedagogical criteria of the learning objects from the most important to the least important for the learner. On the other hand, this hybridization makes it possible to identify the most frequent and most uniform preferences in terms of media and level of complexity of the learning objects, in order to improve the learning experience in the e-learning platform.

5. CONCLUSION

Recommender systems have become a promising solution for improving the effectiveness of e-learning systems. The learner's profile is the basis of any recommender system for CEHL, because based on the profile, the system can suggest personalized learning objects that are more suitable for the learner. On the other hand, the lack of information, especially those related to the learners' preferences, can handicap the functioning of the system and consequently the recommendations will be less personalized.

In addition, recommendations in e-learning are more complex, unlike the recommendations used in e-commerce, which are limited to the selling and buying of items. However, in the learning environment a set of indicators comes into play to generate more precise recommendations. For this reason, we have highlighted the importance of identifying the objective preferences of learners from the ratings they give. These preferences are linked to the pedagogical criteria of the learning objects preferred by the learners.

To this end, we have proposed a hybrid recommendation model, which not only relies on the subjective preferences of the learners expressed by ratings ranging from 1 to 5, but our system also refers to the objective preferences that are induced in an implicit way through the use of the Shannon entropy method, in order to generate more accurate and transparent recommendations for the learner in the learning system.

The k-means clustering algorithm allows us to group learners with similar preferences into clusters, in order to recommend to the active learner new learning objects that he/she has not yet accessed, and that have been well rated by his/her closest neighbors. The results obtained in the experimentation phase illustrate the importance of hybridizing objective and subjective preferences in the recommendation process, to clearly identify their trends and future needs, as well as to improve the accuracy of assigning learners to the most appropriate clusters.

In our future work, we plan to study the recommendation of sequences of learning objects, based on the dynamic prediction of the learning strategy adapted to the learner, through evolutionary meta-heuristic algorithms such as: Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).

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