An Automatic Recommendation Process to Generate Learning Paths Based on Learner Preferences

Hicham Aberbach*, Abdelouahed Sabri, and Raja Marappan

***Abstract*—In the last few years, recommendation systems have become very important and nowadays represent a huge opportunity for e-commerce, social networks and especially e-learning. In particular, it is a commercial tool that increases the revenue of companies, it facilitates the life of users by offering suitable products or services to all Internet users. Moreover, the interest of recommender systems in the context of learning, and in particular distance learning, is that they transform the normal learning system into a personalized learning system. In this paper, we present a new learning path recommendation system based on both the coefficients and scores we have assigned to each topic included in a learning path and on the scores assigned by learners to each topic, expressing their level of interest in a specific area. This system processes a set of input data that are composed on the one hand: parameters resulting from the profiles of the learners, these parameters are scores assigned by each user to each topic, and on the other hand, data related to the learning paths, which show the score or a coefficient that we have assigned to each subject included in the learning path. The objective of this work is to have a system that returns results in the form of appropriate recommendations to each learner who wishes to take courses on a given topic. The results obtained will allow us to have an overview of the preferences and characteristics of the learners in order to better guide them in their educational adventure in each learning path. In fact, this demonstrates the effectiveness and importance of our presented methodology.**

***Index Terms*—Recommendation system, algorithm, personalized learning, recommendation approach, e-learning**

I. INTRODUCTION

A recommender system can be considered as a specific form of information filtering that aims to present a user with items that are likely to be of interest to him, based on his preferences and behavior. These systems have introduced notions inherent to recommendation, based, among others, on information filtering and retrieval, collaborative approaches, machine learning, and they are present in different application cases. We note from our research that e-learning, or learning in general, is one of the main areas where this notion is applied through the design or the development of recommendation systems for use in hybrid training courses. Aleksandra and Boban *et al.* [1] propose recommendation systems which are strongly dependent on the context or field in which they are operating, and it is frequently impossible to transfer recommendation strategies in different contexts. Recommendation systems are changing the way websites and users communicate with each other. They can sort through massive amounts of data to identify user interests and facilitate information retrieval [2]. Paritosh and Thomas [3] provides an intelligent recommendation system by estimating the scores of frequent segments. Implementation was tested on different data sets with different groups of learners. The main objective is to suggest to learners essential learning activities based on their ability to learn as well as their learning style, interest classification, and skills [4].

The goal of a recommendation system is to provide to users personalized recommendations for products or online services to improve customer relationship management and also to solve the problem of information overload. Recommender system proposed in [5] aims to solve the problem of information overload which is considered as a potential issue to many Internet users. Indeed, the system search for information through huge data generated dynamically to provide users with personalized content and services. Today, recommender systems are highly appreciated, both in the commercial and research community, where many approaches have been suggested to provide recommendations [6]. In many situations, a system builder who wishes to use a recommender system must choose from a set of possible approaches. Bhaskaran and Marappan [7] proposed a hybrid recommender system that allows learners to use organized learning content in any appropriate course. The proposed system is designed for learners with no programming knowledge. Mainly, it aims to suggest functional and motivating materials for online learners according to their various conditions, preferences, knowledge ideas and other significant attributes. Recommendation technology is a major component of the Internet of Things (IoT) applications, which can offer an improved service to consumers and assist them in accessing information anytime, anywhere [8]. But traditional recommendation algorithms cannot meet the requirements of quick and specific recommendations of users in the IoT environment.

To personalize learning, it is essential to involve learners. In this context, we proposed to use learners' feedbacks to express their interest in the proposed topics. This article presents a recommendation system based on an algorithm allowing to process on the one hand the data of a learner profile, these data are a set of scores assigned to several training fields that the learner has the habit of following or participating in, on the other hand, the second data that our system processes are presented in the form of learning paths containing several training categories, Each is assigned a coefficient that represents the degree of presence of this category throughout the training course, finally the system returns results that allow us to recommend the appropriate learning path for each user through the percentages assigned

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to each course about the user profile.

The rest of the article is organized as follows: the related work part presents a state of the art of recommendation system used in the framework of e-learning and teaching. In the method part, we introduce our method, its architecture, and that in a detailed way. In the experimentation and result section, we present the implementation of our proposed algorithm via a JavaScript compiler, and we expose the obtained results. The final section is composed of a conclusion of our proposed work, with a mention of perspectives.

II. Related Works

This section gives an overview of learning recommender systems based on different approaches and methods, It explains and gives an idea of each approach used, according to [9], the principle of this system is based on the design of a trace-based model, to follow the user in order to detect his learning style and adapt the course afterwards according to his style. Especially knowing that the learning style is considered to be a characteristic that can change during a training course. So, the objective is to follow the learners in their learning and that goes through three phases: the first is the test for the detection of the initial learning style then in the second phase the preprocessing of the data to extract the different characteristics by observing the different behaviors of the user during a training and then at the end and using the Bayesian network to change the characteristics of the latter to have the new learning style. Recommendation approach is based on the self-organization of learning objects (LOs). Self-organization of LOs means that LOs interact with each other spontaneously and autonomously. Such self-organizing behavior is conducive to the generation of a stable LO structure through information propagation [10]. Tarus and Niu *et al.* [11] recommend e-learning resources to learners, authors proposed a hybrid recommendation system which uses ontology for modeling and representing domain knowledge about the learner and learning resources, while the SPM algorithm discovers sequential learning patterns of learners. System presented in [12] recommends educational resources such as relevant courses to learners enrolled in e-learning paths. They combine content and collaborative filtering and they use association rules. The proposed algorithm was tested free and open education platform Shanghai Lifelong Learning Network. The experimentation shows that this recommendation system can increase the usage rate of educational resources and also promote learners' autonomy and learning efficiency. The system proposed in [13] aims to allow learners to find and choose learning materials that are relevant to their field of interest. It is established on an appropriate recommendation technique of the learning system features. The first significant property of this system is the common ontology for the learner and the learning materials. The second property refers to the pedagogical model developed to make a recommendation. The learning resources are filtered according to the preconditions of the learner's request and knowledge. The learner can request any activity, such as an example or a description, using the graphical user interface. An approach that focuses on the design of a personalized e-learning system based on the Felder and Solomon model and collaborative filtering techniques is presented in [14]. To select the most appropriate learning objects, a recommendation system that focus on the learner's profile is proposed in [15]. An online learning system is presented in [16], which allows an adaptation at the same time to the learners and the openness of the Web, with an accuracy of the difference between the formulation of recommendations in distance learning and several other areas. The main objective the study presented in [17] is to introduce a Hybrid system which combines the self-organizing map (SOM) of a neural network with the data mining (DM) approach for the course recommendations of the eLearning System. Proposes using web mining techniques to construct an agent that would recommend e-learning activities or shortcuts in a course website on the basis of learners' access history in order to facilitate the navigation of the course material and to assist the e-learning process [18]. To improve the relevance of the proposed content, Baidada and Mansouri *et al.* [19] proposed a hybrid method of recommendation that consider in the same time the learner's preferences and similarity with his group. S. B Aher and L. M. R. J. Lobo [20] propose A combination of machine algorithms to find the best way in recommending the courses to students in E-learning. The used machine learning algorithms are ADTree classification algorithm, Simple K-means Algorithm & Apriori. The approach proposed in [21] is builds on the collaborative filtering approach and some characteristics of e-learning. Actors' roles and their interests as well as the representation of the learning resources are used in this approach where the concept is to exploit, on one hand, roles and interests to aggregate the actors in communities of roles and/or interests to make an initial recommendation. On the other hand, the metadata descriptions are used for recommending a new added learning resource (when we have an evaluation about it) to appropriate users by calculating the similarity between the metadata of the new resource and the metadata of other resources that are considered the favorite by the actors. An approach for learning resources recommending using social information present in social networks is presented in [22]. Herath and Jayaratne [23] use web mining techniques in an e-learning environment to provide recommendations to e-learners according to their browsing behaviors, web content, performance, and profiles. This means that the personalized course content is delivered to the online learner. The proposed approach in [24] proposes an architecture offering semantic recommendations using virtual agents, i.e. a virtual recommendation system, which serves to present university students with the most appropriate courses in a real context, taking into consideration their requirements and preferences. This system helps to improve skills more flexibly and facilitates the choice of pedagogical content so that the learning process can take place in the best possible conditions, according to the interests and preferences of the users. Presents a solution to the problems of e-learning recommendation on the Self Directed Learning (SDL) method, exploited to achieve the objectives with the help of Recommendation System (RS), namely Personalized Self Directed Learning Recommendation System (PSDLR), finally this PSDLR system provides comprehensive and personalized recommendations to self-directed learners, to help them overcome the difficulties in selecting learning content [25]. The presented framework recommends a personalized set of videos to customers based on their previous activity on the site and leverages a domain ontology and user item content for domain concepts. To assess the performance of the system, item predictions are performed using the proposed model, and performance is determined by comparing the predicted and actual item evaluations in terms of predictive accuracy, precision, and recall metrics [26]. Aberbach and Jeghal *et al.* [27] proposes a new method of learning personalization based on the calculation of the appropriate learning speed for each learner. Through this learning speed, a learner is affected to a convenient learning level. Aberbach and Jeghal *et al.* [27] provides an adaptive recommender system to predict suitable learning paths for each college-preparatory year learner. Data mining has been widely used in Educational Data Processing where EDM tools are used to explore knowledge [28]. Thus, to extract relevant features and build a customized model for each educational module, various data mining techniques have been proposed ion [29].

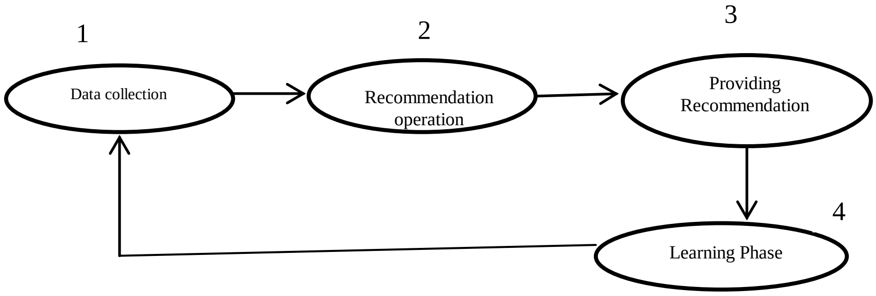

Fig. 1. Recommendations process phases.

III. Proposed Method

Our contribution consists of the implementation of a new learning path recommendation algorithm. Our system allows the process of a set of input data which are composed firstly: from the parameters resulting from the learners' profiles, these parameters are scores attributed by every user to each topic, and secondly, from the data relative to the learning paths, which shows the score we attributed to each topic included in the learning path.

A. Recommendations Process Phases

In general, Fig. 1 shows four stages of our system, the first one is information collection where we will set up the user profile data in association with the parameters of the learning paths, the second stage is called the recommendation where the recommended treatment is performed, then the third stage is dedicated to the display of the results obtained after the prediction operation and finally, after all these phases the learner will be able to start his learning path according to his preferences.The novelty of our system is that it recommends learning paths and not just courses.

This Fig. 2 represents the recommendation process, going through our algorithm presented in the diagram under the name of a recommendation system, then the input data composed of learner profiles with their preferences and an assignment of a score or coefficient for each preference or criteria, and as a result after processing all these data our system returns a set of recommendation based and scores through which we can recommend learning paths appropriate to the preferences of each learner.

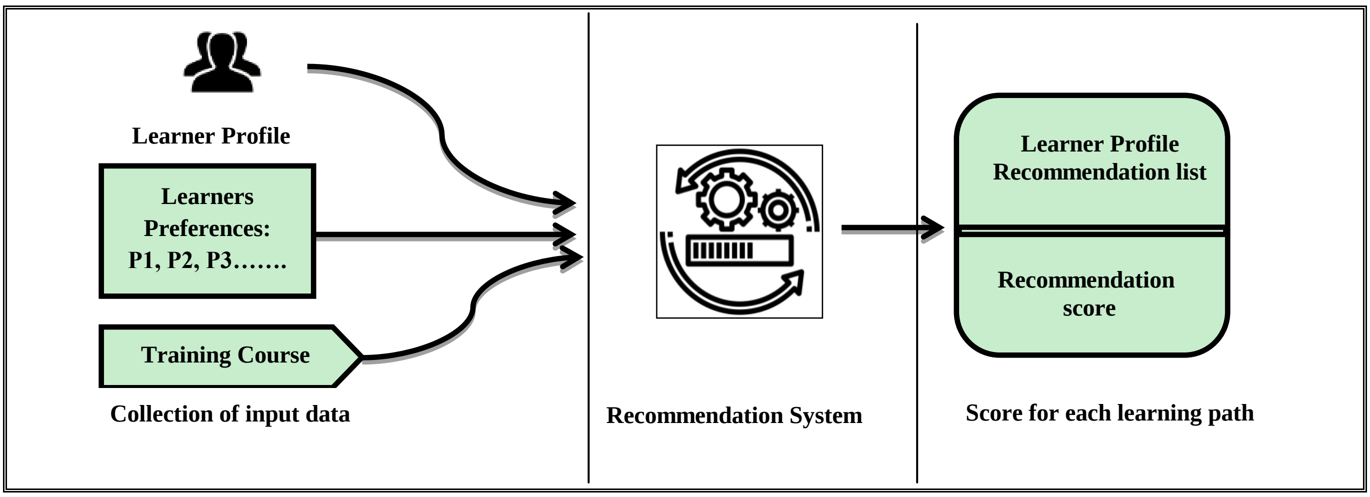

Fig. 2. Proposed recommendation process.

B. Profile Learners

In this section we present the input data, or what we called our Learner Model, this Table I presents a set of scores assigned to a set of preferences that signify training areas, In a general way, scores (N) ranging from 0 to 10 is assigned by each learner to show the degree of interest that each participant has for all of the themes, which could constitute the learning paths. Table I presents the profile learner 1, which demonstrates different scores assigned for each theme.

TABLE I: PROFILE LEARNER

Learner "1"	Score(interest for the subject) N, 0⩽N ⩽10)
Communication :	10
Computer Science:	0
Statistics :	0
History and Geography:	7
Mathematics:	0
Languages:	8
Web technologies:	0

C. Training Path Parameters

The second part of this section presents the training pathways which are composed of a set of themes, which will be dealt with later during the pathway, each theme is assigned a coefficient out of an average of 10 to show whether the theme is dealt with in the pathway or not, and if it is dealt with a score out of 10 is assigned. We mention that we chose to set coefficients from 0 to 10 as a number on an average of 10, which indicates the presence of the topics during the proposed learning paths. This Table II shows the training path parameters which describes what we have explained before:

TABLE II: TRAINING PATH PARAMETERS

Training Path "1":	Coefficients(C), (0⩽C⩽ 10)
Communication :	10
Computer Science:	0
Statistics :	0
History and Geography:	8
Mathematics:	0
Languages:	10
Web technologies:	0

Fig. 3 shows the result of the processing of our input parameters that we were able to integrate into our algoritmge as you can see, the translation of data from tables into code looks as follows:

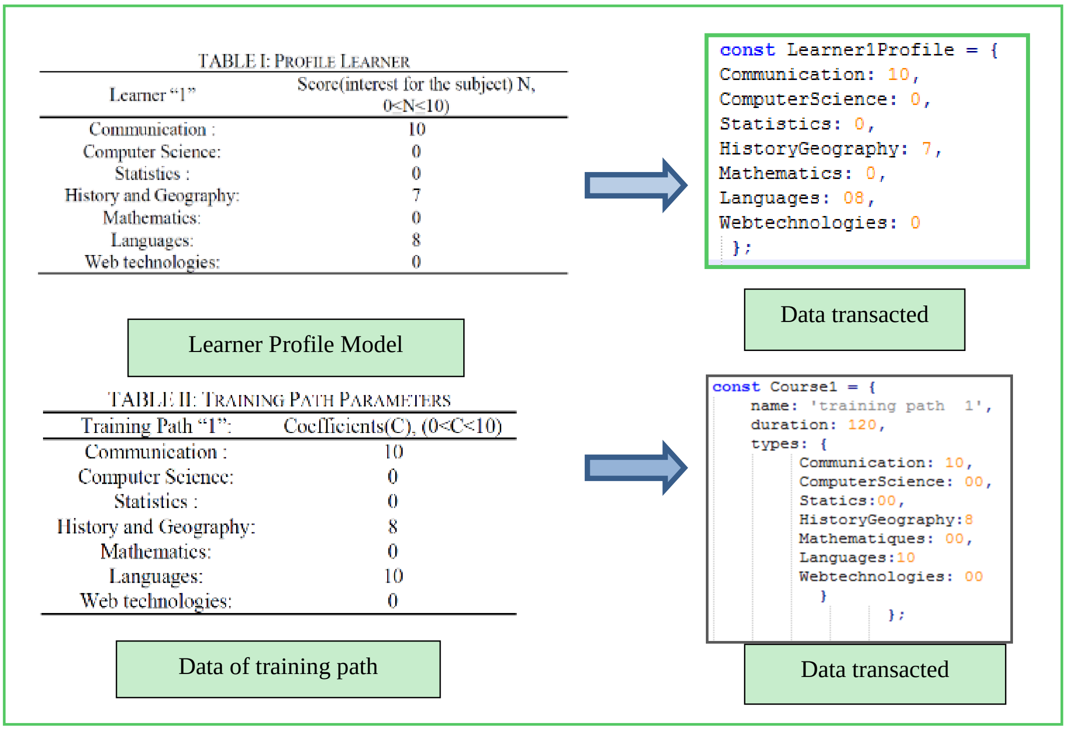

Fig. 3. Transaction of our data.

To clarify where the data comes from and all the parameters that we have put in the previous tables, for the parameters of the learning paths are given by the teacher responsible for these paths, and for the data relating to the profile of the learner, are given from the learner himself before starting any course, both types of data present our input settings appropriate to our algorithm.Coefficients as values presenting the degree of willingness to pass a course that contains all the themes, for example for the learner1, we find that he expresses his choice to follow training courses integrating the themes of communication, history and geography and languages, the other themes he assigned 0, which means that he is not interested in training that contains this kind of subject.

For example: in the learner profile Model parameter, we have 10 for the theme communication, this means that this learner wishes to follow the future learning paths dealing with the theme communication, on the other hand, the number 0 means the opposite of this idea.

D. Algorithm Method / Functional Architecture of the Algorithm

The Fig. 4 shows all the steps in our method, starting with the input data and ending with the desired results. These results are scores assigned to each learning path.

The principle of the algorithm is to personalize learning by highlighting the scores attributed by learners to the different paths. Thus, the score of each topic listed in the learning path parameters will be weighted by the score assigned by the learner. The score of each path is the average of the weighted scores of the themes that make it up. Finally, the result will be the percentage scores of all the paths. The algorithm displays the results after recommendation processing, consisting of the scores presented as percentages assigned to each learner for each learning path.

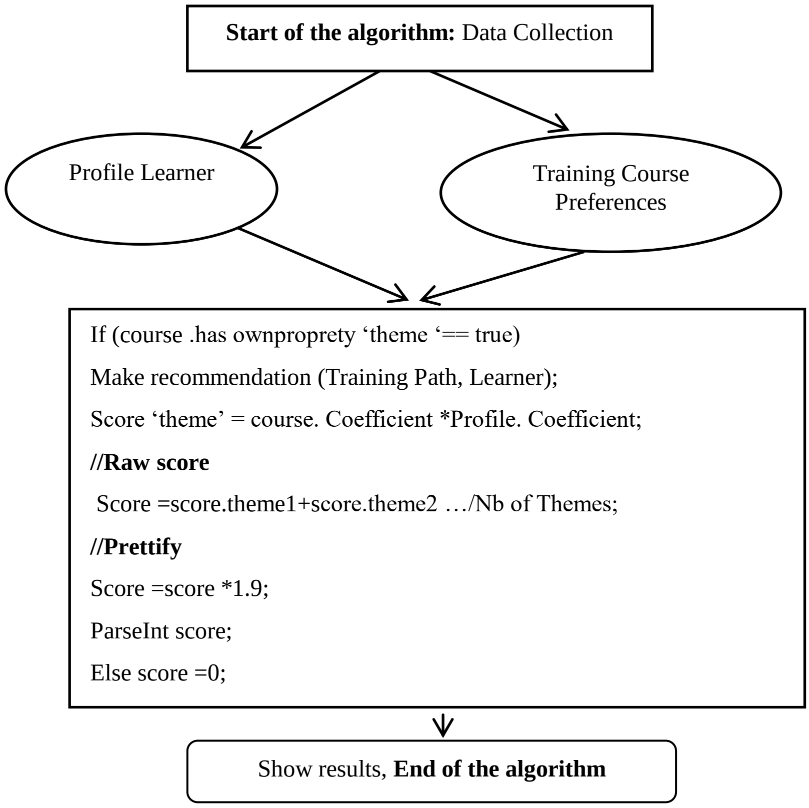

Fig. 4. Steps of the algorithm of our method.

IV. Results and Discussion

In this part we will run and test our algorithm on a JavaScript compiler, we will have as input data the profiles of the following learners: Table III presents profile learner 1, learner 2, and learner 3, the table presents the preferences of each learner for each theme with an attribution of scores from 0 to 10.

The tables III and IV represent data that are oriented towards practice and experimentation, in order to apply the method of our calculation described in a general and theoretical way in the section algorithm method.

These values are scores assigned by the participants or learners showing the degree of interest in each topic, these numbers are on an average of 10. For the learning paths data, we are going to use the following data tables, these parameters are provided by the learning paths responsible, Table IV presents the scores assigned to the themes of learning path 1, the scores for the learning path 2 and the scores assigned to the themes of learning path 3.

TABLE III: Profile Learner

	Profile Learner : Learner1	Profile Learner : Learner2	Profile Learner : Learner3
	Score (interest for the subject)		
Communication :	10	00	0
Computer Science:	0	10	0
Statistics :	0	10	0
History and Geography:	7	8	10
Mathematics:	0	10	7
Languages:	8	9	10
Web technologies:	0	7	3

TABLE IV: Training Path

	Training Path "1":	Training Path "2":	Training Path "3"
	Coefficients(C), (0⩽C⩽10)		
Communication :	0	10	0
Computer Science:	10	2.5	10
Statistics :	0	00	10
History and Geography:	0	1.5	0
Mathematics:	8	0	0
Languages:	0	8	0
Web technologies:	8	00	8

After the processing of all this data through our system, we will get the results that will allow us to give recommendations about the level of interest that a learner will have in a learning path. This interest is expressed through a percentage assigned to each learning path and corresponding to every single learner.

In the rest of this section we present the results achieved in the experiment of our new approach: Table V shows the result of our experimentation on learner 1,2 and 3 for the three training paths For the first learning path, the results of our learning system show that Learner1 does not have interest in this course, but Learner2 and Learner3 will have an interest which is reflected in these respective rates of 36.91% and 21.71%, Concerning the second course, the interests resulting from the treatment of our system are as following: Learner1: 47.36%, Learner2: 22.79% and Learner3: 25.78%. And for the third learning path, the following results are obtained: Learner1: 0%, Learner2: 42.34% and Learner3: 6.51%.

TABLE V: RESULT OF EXPERIMENTATION

Training path 1	Training path 2	Training path 3
Sabri conducted all steps of the research		
Learner1: 0%	Learner1: 47.36%	Learner1: 0%
Learner2: 36.91%	Learner2: 22.79%	Learner2: 42.34%
Learner3: 21.71%	Learner3: 25.78%	Learner3: 6.51%

From all of the above, our system allows for recommendations about the preferences of each individual learner regarding the topics they desire to be included and treated in the learning paths, This can be used in the e-learning platforms, in learning applications, to get an overview on the interest of learners or normal users wishing to follow any kind of learning path. It will save time and ensure the attention of the learner, which is the most difficult thing to obtain in an online course.The strength of our method compared to existing approaches is that it offers useful recommendations for the teacher, allowing him/her to have an idea of the learners' preferences regarding learning paths and not only a recommendation on a specific course, the aim of this contribution is to recommend entire learning paths and not only courses. It should be noted that course is part of the learning or training path. And by comparing our method with others, we have discovered that our system takes into account the preferences of each learner before starting the learning process, something that is not taken into account in other related methods. In fact, according to the experiment, the learner will be able through our system to follow and participate in the learning path of his choice, which increases the effectiveness of the training and respects the preferences appropriate to each learner, The results found show the adaptability and the effectiveness of our method since it gives the degree of interest that each learner will bring to each learning path, and this will facilitate the assignment of learners to appropriate learning paths.

V. CONCLUSION AND FUTURE WORK

Successful learning is that which responds to the learners' preferences and immediately meets their needs, in order to facilitate the learning process, whether it is online or face-to-face learning. We are talking about personalized learning, which draws its effectiveness from recommender systems designed to provide learners with relevant and user-friendly educational content. In this paper, we were able to develop a new e-learning recommendation system to provide recommendations for learning topics and courses that attract learners. The approach is presented as a new system that processes the input data of a learner model, to produce percentages showing the level of interest of each learner model for each proposed learning course. This method is part of the solution to the problem of sustained attention and motivation that learners lose during an e-learning course. It also increases the quality of learning recommendations, especially from a pedagogical point of view. As a perspective, we plan to implement our system on an e-learning platform to test and evaluate it.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Abdelouahed; Raja Marappan analyzed the data of entries and Aberbach Hicham processed, prepared the database and wrote the paper; all the authors had approved the final version.

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