Context and Learning Style Aware Recommender System for Improving the E-Learning Environment

https://doi.org/10.3991/ijet.v18i09.38361

Khalid Benabbes[1(✉)], Housni Khalid[1], Zellou Ahmed[2], Brahim Hmedna[3], Ali El Mezouary[4]
[1]MISC Laboratory, Faculty of Sciences, Ibn Tofail University, Kénitra, Morocco
[2]SPM Research Team, ENSIAS, Mohammed V University, Rabat, Morocco
[3]IMIS Laboratory, Faculty of Sciences, Ibn Zohr University, Agadir, Morocco
[4]IRF-SIC Laboratory, EST, Ibn Zohr University, Agadir, Morocco
khalid.benabbes@uit.ac.ma

Abstract—The learning management system (LMS) is an e-learning software that raised the interest of disparate learners' groups. However, learners have difficulties in finding learning resources tailored to their preferences in the best way at the right time. Making the learning process more efficient and pleasant for learners can be achieved by using context and learning styles such as customizing aspects. This study proposes a new data-driven approach to retrieve learners' characteristics using traces of their activities based on the Felder-Silverman Learning Style Model (FSLSM). In this research, the traces of 714 learners who enrolled in three agronomy courses taught at IAV HASSAN II (winter session 2019, 2020, and 2021) were analyzed. Learners are categorized into clusters by their preference level for global/sequential learning styles, using an unsupervised clustering method. Then a classifier model tailored to our requirements was trained and based on the learner's learning style and their current context, a learning object recommendation list is proposed for them. The results revealed that the k-means algorithm performed well in identifying learning styles (LS) and the use of context features defined from the learners' adaptive close environments improved learning performance with an accuracy of over 96% given that most of the learners preferred a global learning style.

Keywords—E-learning, recommender system, context, learning styles, decision tree rules, dropout

1 Introduction

The Learning Management System (LMS) is a new and popular platform dedicated to e-learning. This e-learning environment has encouraged a wide community of learners to take a lot of free courses [1]. LMS platforms collect and save huge datasets from learners' actions, which can provide an overview of learning processes [2]. LMS learners are disparate across preferences, knowledge, and skills. For instance, some learners prefer using videos and images to study (visual learners), while others prefer to use audio and text to learn (verbal learners). The gathered data allows us to identify the mode of the learner's study. Thus tailoring learning experiences to give learners more adapted learning content to their learning style and context rather than providing the same content to all learners. This can improve learning satisfaction and increase teaching effectiveness [3] as well as the course completion rate (less than 15% [2]).

For some researchers, the quality of educational service relies on the ability of the system to provide learners with the most appropriate resources for their learning style at the right time and in the appropriate ways [4]. This requires first identification of the learner's learning style. Therefore, two approaches have been proposed; the automatic approach [1] and the collaborative approach [5]. The automatic approach updates dynamically learners' traces of behavior and activities within the learning system to build the learners' model and identify the learning style. This approach is more efficient in classifying the learners as it uses the data to track learners' learning styles in real time. The collaborative approach, by offering a static model for learners, focuses on a survey that asks learners to fill out a questionnaire. Most learners select random responses due to the many questions and their unawareness of the meaning and impact of the questions. This approach is less effective because it is difficult to motivate learners to complete the questionnaire. In addition, learning styles are static and unchangeable over time [6]. To overcome this issue, automatic methods have been developed to identify learners' learning styles by using the history of their activities in the LMS [7].

Traditional learning systems focus on the learner's profile without taking into account the context. Our new approach aims to recommend resources related, not only to the learner's learning style but also to his current context (time, mobility, physical environment, brightness, noise, place, etc.).

This can lead to adapting learning objects (LOs) to the learners' current context, without any explicit intervention from the learner [8]. That makes it an essential factor to enhance the efficiency and operability of the system. To conduct this research, the decision tree technique was applied, based on designed adaptation rules for the learner contexts. This is constructed on a scoring method for ranking the recommended resources.

The sequential/global learning style of learners is identified using the traces taken from agronomy courses delivered at the IAV HASSAN II (sessions of winter 2019, 2020, and 2021). For this purpose, four clustering and classification algorithms of learning styles were compared to justify our decision to use the k-means and the decision tree to create a prediction model of learning style and context with high accuracy.

This research aims to tackle these research questions: how to automatically identify the learners' learning styles? How to recommend learning resources to learners using their preferred learning style and contextual features?

2 State of the art

In this part, we will discuss the learning style concepts and the most popular approach for identifying them. After that, we will explore the clustering algorithm applied to the learners' traces produced during their interaction with the e-learning platform, as an automatic approach to identify learners' learning preferences, as well as the methods frequently adopted in the context-aware learning recommendation systems.

2.1 Learning styles

Learning style was initiated in the field of educational psychology in the 50s and was used for the first time by Herb Thelen [4]. It refers to the collection of behavioral qualities that persons exhibit in a given situation that separate them from others [6].

A nested model of learning style provides a wide range of learning orientations and makes the same instructional strategy beloved by some students and detested by others [7]. Several models of learning styles have been put forth by psychologists. The models proposed by Felder and Silverman [9], Honey and Mumford's model [10] Dunn and Dunn's model [11], Kolb's model [12], and VAK/VARK model [13] stand out in this line.

Four dimensions are used to classify learners' learning styles following the model developed by Felder and Silverman [9]. There are some opposing learning styles in each dimension. For instance, the understanding dimension offers both sequential and global teaching styles. The processing dimension has an active and reflective teaching style. Felder and Soloman [14] created the Index of Learning Styles (ILS) to discriminate different learning styles within this approach. It has 44 questions (11 queries for each dimension) and every item has two options. The score between +11 and –11 is provided for each dimension as per the preferences of the learners. Three preference levels are employed for each dimension to further divide learners' preferences at a higher level.

The moderate category's score ranges from –5 to –7, or from 5 to 7. Per dimension, the balanced category receives a score between 3 and –3. Finally, the score ranges from 9 to 11, or from –9 to –11 for the strong category [7]. For our research, the FSLSM approach has been selected for these reasons: (1) the four dimensions of this model are independent and discrete; (2) a variety of researchers agrees that the ILS is valid and reliable for evaluating learning styles; (3) the FSLSM makes a granular categorization of learning styles by plotting each dimension on a scale of –11 to +11 and (4) the learning object is recommended using customized content in learning systems (Figure 1).

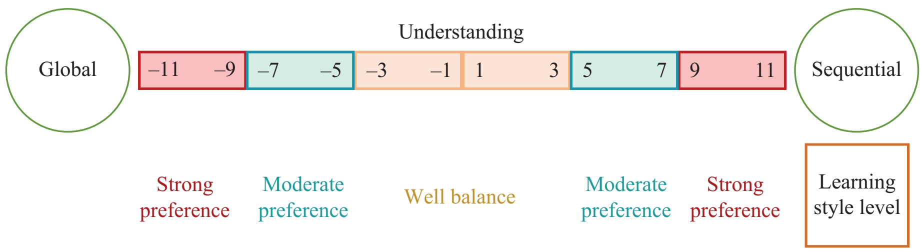

Fig. 1. Scales of learning style understanding dimension

According to Honey and Mumford's model [10], there are four main learning styles, these are Reflector, Activist, Pragmatist, and Theorist. For the Dunn and Dunn model, there are five dimensions of learning styles namely Environmental, Emotional, Sociological, Physiological, and Psychological [11]. Kolb's model is a theory of learning that suggests to learners experience new information and ideas, think about them, reflect on them and apply them [13]. The VAK/VARK model is defined by the following learning styles: Kinesthetic learners, Visual learners, and Auditory learners [13].

The last three models are easy to be understood and may be used in many contexts, such as education, vocational training, and personal development. They also can reinforce the multi-skilling and the individual's resilience. However, it is difficult to use them to identify learners' preferred learning styles accurately [15].

2.2 Learning objects

A learning object (LO) is defined as a digital or analog entity that tends to be exploited or reused within a learning activity through a technology environment [16]. It can be considered as a course, case study, document, exercise, classroom presentation, etc. A learning object is also described as small educational components making up a course (content, activities, global or sequential content), that can be reused in various learning contexts [17]. The learning objects can be shared and reused through the description of these objects, to be indexed in a database [16]. The researchers aim to describe the learning objects with the metadata [18]. Given that the current version of the Learning Object Metadata standard proposed by the Dublin Core is determined in the form of 45 descriptive elements categorized into 9 groups: General, Classification, Reviews, Learning Information, Overview, Metadata, lifecycle, relationships, and privacy requirements [19]. The current learning object recommender systems are designed to give good learning objects to the right learners, based on the learners' objectives, and using the similarity distance computation [19]. A scoring system for assessment is often used in object learning in various models, based on the learner's appreciation degree on the Likert scale [19], to make sure the learning resources provided are suitable to learners' interests.

2.3 Learning recommendation context

Context-aware recommender systems provide limited courses for the current context, making them better rankers than other resources. For instance, if learners with a similar profile rated a course in various contexts, it will not be recommended to them because of the contextual difference. Therefore, a context-based recommendation can satisfy the real and effective expectations of the learner [20]. A contextual learning system is any learning environment that allows learners to access learning content from anywhere at any time, whether mobile devices or wireless communications are utilized or not. The system can detect the users' environment and react accordingly since users may have many considerations according to their particular contexts and they want them to be distinct [21]. This includes the detection, acquisition, and interpretation of context elements and their changes. Then the recommendation of learning resources is adapted to the learners' preferences based on their current context. In this way, the system not only reduces the amount of time spent on research but also provides them with suggestions that would not have been spontaneously taken into account. Two approaches can be used to classify recommender systems and these are content-based recommendations [17] and collaborative filtering [22].

The traditional collaborative recommender system is User × Item = Rating. This formula has been improved by integrating contextual information as such User × Item × Context = Rating.

Contextual information is used in addition to the user and item to assess items that the user has never seen [17]. Contextual information is provided as implicit or explicit. Implicit information (temperature, noise, connectivity, luminosity, location, mood, time, etc.) can be collected by IoT sensors [23]. In contrast, explicit information is produced when the user puts personal data into the system (last name, first name, birthday, hobbies, gender, etc.) [8].

2.4 K-means clustering algorithm

A dataset is clustered after it has been organized into groups satisfying two requirements: (1) increased spacing between classes (separability) and (2) reduced separation between items belonging to the same class (compacity) [24]. Clustering can identify the hidden structure of the set of data; this is useful in areas where the dataset is non-labeled. Agglomerative [25], k-means [26], DSCAN [27], and Birch [28] are the clustering algorithms that use various features such as centroid-based clustering and connectivity-based clustering. In this approach, we will focus on clustering with k-means (Figure 2). It is listed as one of the most well-liked clustering methods by Vankayalapati et al. & others [26]. According to Khan [29], with this algorithm, the locations of the cluster centers and the distribution of each node within the cluster are adjusted iteratively.

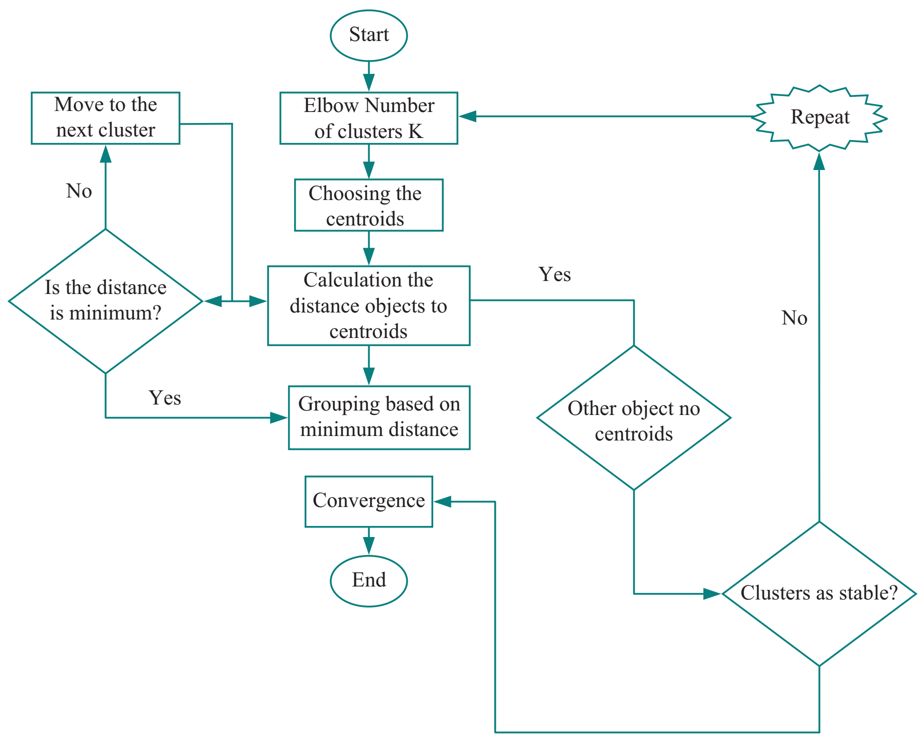

Fig. 2. K-means algorithm's logigram

3 Related work

In this section, the automatic approaches (Table 1) for the identification of learning styles using FSLSM dimensions as discussed. Choi & Kim [30] tracked learners' activities in e-learning and as a result of their studies, they proved that Bayesian networks are efficient for identifying learners' learning styles for Sequential/ Global (S/G), Active/Reflexive (A/R), Visual/Verbal (V/V) and Sensitive/Intensive (S/I) dimensions of the FSLSM.

AL-Fayyadh et al. [31] suggested an approach based on a neural network algorithm to automatically identify the learning style constructed on learners' interactions with the e-learning system. This approach has proven its performance with an accuracy of more than 69.3% on the four learning style dimensions S/G, S/I, A/R, and V/V.

Klašnja-Milićević et al. [32] proposed an automatic web-oriented learner model based on the FSLSM model and they opted for an AprioriAll algorithm. The results showed high accuracy for the majority of the learning style dimensions. This was confirmed by evaluating the learning style using the correlation between the learners' learning features of the model and the ones obtained from the surveys.

Bernard et al. [33] recommended an approach that assessed 78 learners, using the artificial neural network algorithm. This approach is efficient, particularly in identifying the learning styles based on the FSLSM model.

Table 1. Insights into data-driven research

Research	Environment	No. of Learners	Algorithm
AL-Fayyadh et al. (2022) [31]	Adaptive educational hypermedia system	86	Multi-layer feed-forward NN (hidden units: 24)
Choi & Kim (2021) [30]	E-learning courses	32	Bayesian networks (BN)
Klašnja-Milićević et al. (2011) [32]	E-learning system	340	AprioriAll algorithm
Bernard et al. (2017) [33]	Learning management system Moodle	78	Artificial neural networks (ANN)

4 Methodology

4.1 Identification of learning style

This section introduces our suggested methodological approach with seven steps (Figure 3). It aims to group learners according to their preferences for understanding the FSLSM dimensions. It begins with the extraction and pre-processing of raw data for each learning style understanding dimension of FSLSM to transform each learner into a set of corresponding features. Then, the unsupervised clustering algorithm is implemented to group learners according to their preferred degree in the learning style.

Finally, the recommendation of learning resources will be considered based on the learners' learning styles.

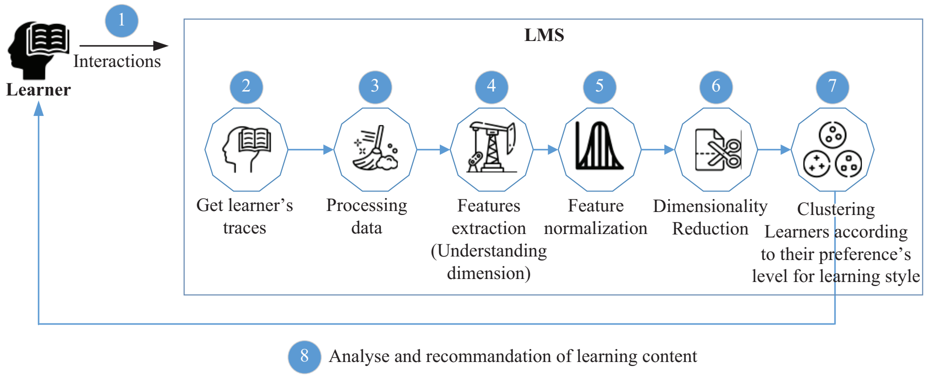

Fig. 3. Process of the proposed learning style identification approach

Pre-processing. This stage was conducted to improve the quality of the data to be handled. First, we retrieved the learner traces produced during the session of winter 2019, 2020, and 2021 from the original raw data. Then we continued with the cleaning to improve the quality of the data by removing redundant information. Each flow event was assigned to the week in which it was performed and then it was mapped to a daily session. The reconstruction of the sessions using the concept of the difference between two timestamps supposes that each page visited session should not be longer than one hour, the sessions have been reconstructed. Then each resource was linked to the learning object format, using the "Resource_display_name" property. In the following section, we will discuss feature extraction, normalization, dimensionality reduction, and the clustering algorithm used to define which learning style is most dominant across the balance between global and sequential learning styles.

Feature extraction. Selecting the most appropriate model from existing features to perform a particular task is called the "feature extraction" technique [5]. Therefore, a feature engineering process termed "knowledge zone" is applied to build a set of features used in machine learning algorithms, which is executed by adding features one by one in a recursive way until the minimum number of features is obtained [34].

For this purpose, the traces of each learning style were collected from the Moodle LMS. Then, for each learner, feature sets extracted from the dataset were processed and associated with the learning style features of the FSLSM comprehension dimension.

The potential features for the FSLSM comprehension dimension are outlined in Figure 4:

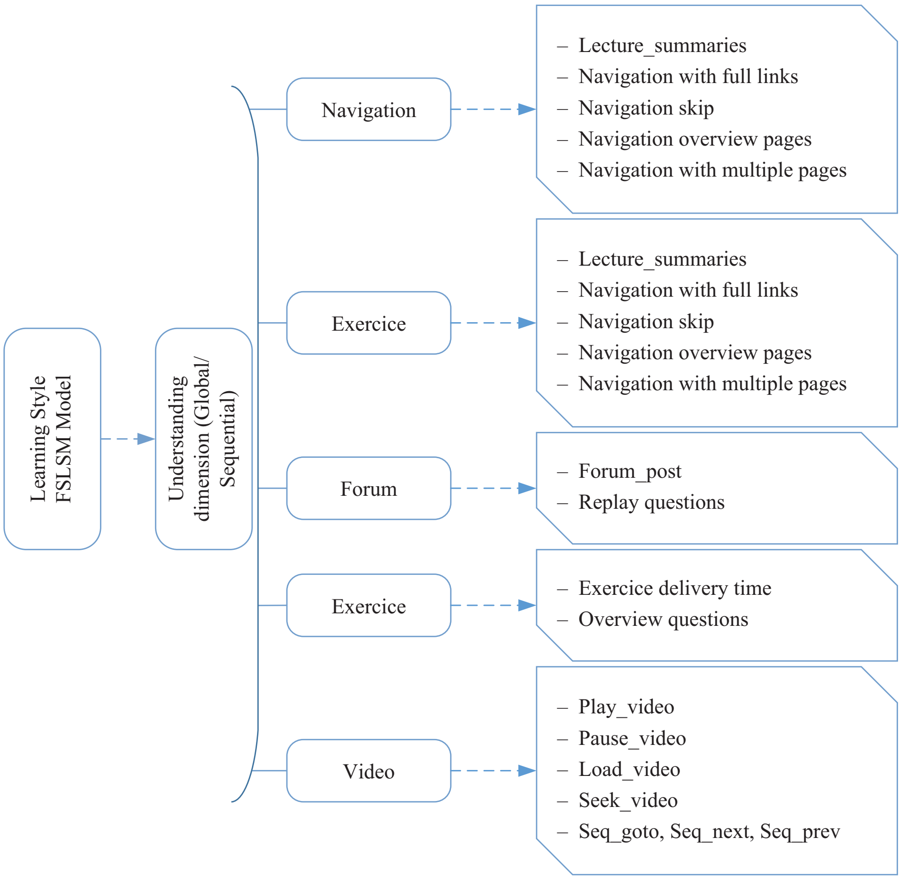

Fig. 4. Modeling learner interactions with understanding dimension in the Moodle environment

Sequential learners are reported to use frequently the next and previous buttons to move through the courses' sections [32]. They are intended to use the forums to review topics, post, and respond to questions in depth [15]. In contrast, global learners are reported to read discussions globally and reply shortly to a given post.

Feature normalization. Normalization is a technique used to decrease the impact of features handled by the learning algorithm. To take measures, the MinMaxScaler function that is available in Sklearn [34] is used to scale the features between 0 and 1. This function executes the following equation:

$$x' = \frac{x - X_{min}}{X_{max} - X_{min}}$$

Where x' refers to the normalized value, x is the actual value of X, X_min, and X_max on the dataset.

Dimensionality reduction. Principal Component Analysis (PCA) is a technique used to reduce the dimension of the features to a 2-D space for each learning style according to the understanding dimension which does not affect the correlations between the data [35].

As a consequence, the different learning styles are plotted in a 2-D space. The results of the PCA are then analyzed to create learners' groups of the highest quality using K-means.

4.2 Clustering and prediction modeling

This section intends to group learners by preferences and degrees according to the Sequential/Global dimension of the FSLSM [34]. After analyzing the learners' features, their traces, and the frequency of their activities in the LMS, several taxonomies and learner profiles were suggested [36], [33]. But only active learners who are involved and explored the most resources in the Learning environment were selected [5]. However, the passive learners who browse content without participating in any of the available activities were excluded. Similarly, drop-ins are a group of active learners who never attended the course. By analyzing the features, behaviors, traces, and frequency at which each learner carries out activities in the LMS (Figure 5), a set of profiles and taxonomies of learners involved in the LMS was identified [20]. The clustering technique was used to automatically define groups of active learners who have similar features. The treated feature vectors are mapped to each learning style for the understanding dimension of FSLSM. Then, the Elbow method is applied to these vectors to determine the right number of clusters. The correlation between the change in clustering cost and the number of clusters was plotted. The value of the average distance to centroids decreases quickly until a particular point, the same as the changing rate, which also decreases later. This point corresponds to the right number of clusters [37]. The cost can then be calculated using the following equation:

$$\text{Cost} = \text{Log}\left(\frac{1}{n}\sum_{i=1}^{K}\sum_{x\in \text{Cluster}_i}\left|x-\text{Centroid}_i\right|^2\right)$$

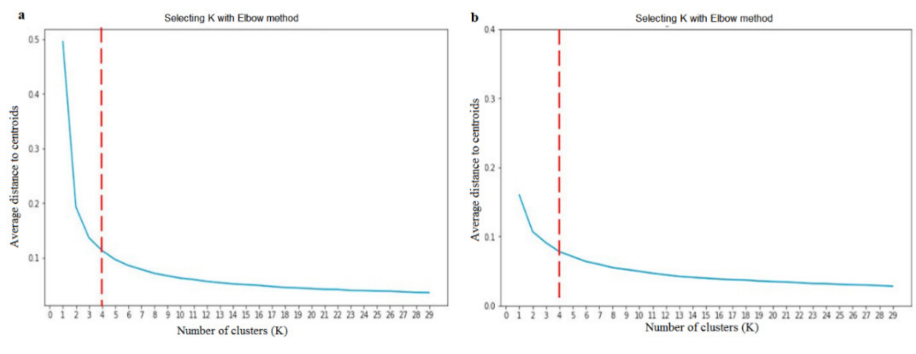

Fig. 5. Elbow point for global (a) and sequential (b) learning style

As shown in Figure 5, the number of clusters selected is four. The study has proven that k-means++ is the most suitable algorithm for setting the initial centroid of clusters. This new version is developed to correct the weaknesses of k-means [37]. The results obtained are a dataset with 593 learners and 9508 events. They are given as learners' traces excluded from the observers. To define a vector of learner learning style features, the two vectors of global_LS and sequential_ LS characteristics were merged using the learning style balancer. This allows us to label the dataset, used as a source of information for the classification algorithms intended to train the prediction model. For this reason, four models of classifiers adapted to our requirements (decision tree (DT), K-nearest Neighbors (KNN), neural network (NN), and random forest (RF)) were trained and compared. These models were trained using k-fold cross-validation with k-value = 10 to evaluate the performance of each one. Then the grid research technique is applied to identify the optimal hyper-parameter of each model. At that time, the learning curve technique is used to assess the underfitting and the overfitting of different models. The accuracy results achieved indicate that DT is more efficient with a high value to become more appropriate for our purpose.

4.3 Context-aware learning object recommendation

In this subsection, we will address the prototype of recommending learning objects to learners. Any learner has a favorite learning method in each dimension of the FSLSM model. In this study, we will mainly focus on the courses that support both sequential and global learners. This subsection is articulated in two parts, the first part is to construct the context model by mining the contextual features, and by listing all the combinations of the various learning objects (audio, video and text), the contextual features, and the learning style. In the second part, a decision tree technique is applied to build a tree base model for adaptive rules, which are used by this system to provide the relevant resources for the learner's profile at the right time in the best way. The correspondence between the original learning styles and the proposed styles is outlined in Table 2. The concept of the proposed draft is inspired by the approach of Gope & Kumar [38].

Table 2. Mapping the learning style of the initial FSLSM model with the adjusted variant [38]

Learner's Interests		
Original Variant		**Edited Variant**
Sequential	Strong/Moderate	Sequential
Sequential/Global	Balanced	Balanced
Global	Strong/Moderate	Global

All structural metadata of a learning object for global and sequential learning styles listed respectively in Tables 3 and 4 are stored in a file called JSON [39] as keys/values delimited by commas easily be scanned for reconstructing the resource structure and calculating the related LS_scores. To access the JSON file, several solutions have been proposed [38]. In our case, we opted for the API/REST [40] because of its advantage of having access to the files through the web browser and its easiness of use. We also chose the JSON file because it is suitable for experimentation and studies, and can be edited in offline mode.

Table 3. Set of meta-data for identifying learning objects for global learning style

LO	Block Metadata
Exercises	Activity, Assignment, Homework
Applications	Programming, Project, Creative, Understanding, Simulation
Videos	Full_training_video, Training_series, Course_series, Conference
Presentations	Exposition, Slide, Plan, Illustration, Graph
Forum	Forum_stay, Proposal_exchange
Discussions	Discussion, Show_answers, Detailed_answer, Answer_changes, Question_answer, Debate, Collaboration
Course_overviews	Course_overview, Course_insight, Resume
Experimentations	Experiment, Lab, Virtual_lab, Practice, Observation, Demonstration, Trial, Study
Applications	Application, Programming, Creative, Understanding
Images	Slide, Illustration, Graph, Poster, Figure, Card, Infographics.

To normalize the LO_scores, each LO's block metadata frequencies are scaled between 0 and 12.

Table 4. Set of meta-data for identifying learning objects for sequential learning style

LO	Block Metadata
Additional_material	Dictionary, Survey, Note, Reference, Research, Database, Diagram, Table, List, Documentation, Think, Concept cards
Outlines	Outline_visit, Summary, Outline_stay
Videos	Video_overview, Short_video, Video_abstract, Video_resume, Video_insight.
Quiz	Quiz, Questions, Quick, Inline
Tests	Test, Self-Assessment, Exam, Review, Evaluation
Audios	Audio_messaging, Audio_information, Audio_training, Podcasts, Recording, Voice_over, Dialogue, Narration, Interview
Forum	Forum_short_visit, Forum_short_post
Course_detailed	Review, Course, Learning, Lesson_narrative
Examples	Example, Model, Project, Method, Tutorial, Function, Working, Basic, Program

The learning object format (video, text, audio, image), made up of learning objects (concepts, exercises, outlines, etc.), defines the resource type offered to the learners based on their current learning context_style vector (Table 5).

Table 5. Relationship between learning objects and their formatting

Image	Video	Text	Audio
Images	videos	Presentations, Forum, Applications, Outlines, Exercises, Course_overviews, Course_detailed, Tests, Additional_material, Experimentations, Discussions, Quiz, Examples	Audios

The calculation of the LS_score of each resource for both LS (sequential_LS, global_LS) was based on the assumption that each LS is supported by some LO. Then, the frequency of the learning objects corresponding to the swept resources was computed. Table 6 displays a mapping list between LS and LO, where the checkmark means that the LO is adapted to the related LS.

Table 6. Relation between learning objects and learning styles

LO	LS	
	Global	**Sequential**
Presentations		⊗
Forum	⊗	⊗
videos	⊗	⊗
Discussions		⊗
Applications	⊗	
audios	⊗	
Outlines	⊗	
Experimentations		⊗
Exercise		⊗
Course_overviews	⊗	
Course_detailed		⊗
Tests	⊗	
Concepts	⊗	
Examples	⊗	
Images	⊗	

As shown in Figure 6 and based on the learner's actions on the LMS, the approach searches for the identification of the learner's learning style across the generated traces and needs by using the LMS user interface. This data is fed to the recommendation generator to produce a list of recommendations, ordered by learning style scores (LS_scores).

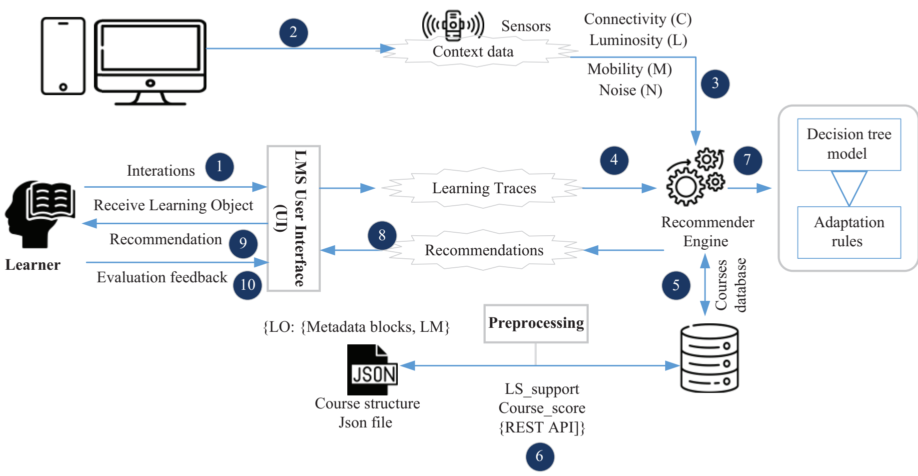

Fig. 6. Learning course recommendation system architecture

By using the learning object pattern and the metadata of a learning resource put in the file named JSON, the preprocessor calculates the learning object scores (LO_scores) for each resource and inserts them into the course database with some descriptive information. Then, it creates the vector of LO_scores for each resource, using an algorithm. For each LO, a LO_score is calculated by analyzing the resource outline considering that each learning object is assigned one of these LS (global/sequential). The recommendation generator selects from the database all the resources that meet the learners' needs, aggregates the LO_scores matching the learners' privileged options and computes the LS_scores for these resources. The recommendations are then offered as a set of resources related to the course selected, with the resources' LS-scores sorted in descending order. In the end, the learner is asked for feedback on the received recommendations to assess the accuracy of the proposed approach (Figure 6).

Context modeling. Our contextual model is expressed as the quintuple V = < L, M, C, N, LS >, where L means luminosity, M is mobility, C is connectivity, N is noise level, and LS is the learner's learning style. Luminosity typically should be between 1000 Lux and 1500 Lux. Studies have shown that high or low light has an impact on learning, and most effort is spent by the eyes [41]. In the case of mobility, the audio-learning object format will be proposed. The text is only attributed if the learner is stopped. In general, the values options are yes and no. For very low connectivity, the e-learning system provides text-format Learning Objects, with attribute values ranging between high and low. The noise usually varies between 70 and 75 dBA. If the noise level is higher or lower than the threshold, it will be trouble for the learner, and consequently, the format of learning object is adapted to the learner. Only, the understanding dimension value of the FSLSM model (sequential, global) is taken into account in this study. Each dimension of the context vector discussed defines the learner's context as a factor to tailor the learning object to the learner's current context. Table 7 illustrates what learning objects format to associate with each dimension forming the context model.

Table 7. Matching rules between context attribute and Learning Object format

Context Dimension	Attribute Value	Learning Object Format
Luminosity	– Yes – No	– Text, audio, video, image – Texts
Mobility	– Yes – No	– Text, image – Text, audio, video, image
Connectivity	– High – Low	– Video, text, audio, image – Text
Noise	– Normal – High	– Text, audio, video, image – Text, image

Decision tree rules. Through the contextual information gathered by sensors, 32 combinations are made up of the different values of attributes (Luminosity, Mobility, Connectivity, Noise, LS) and the learning object formats (video, audio, text, image) as shown in Table 8.

Table 8. Our sample grid of available contextual values

Stage	Luminosity	Mobility	Noise	Connectivity	Learning Style	Learning Object Format
1	Yes	Yes	Yes	High	Global	Audio
2	Yes	Yes	Yes	High	Sequential	Audio
3	Yes	Yes	Yes	Low	Global	Audio
4	Yes	Yes	Yes	Low	Sequential	Audio
5	Yes	No	Yes	High	Sequential	Text
6	Yes	No	Yes	High	Global	Text, Image
7	Yes	No	Yes	Low	Sequential	Text
8	Yes	No	Yes	Low	Global	Text
9	No	Yes	Yes	High	Sequential	Audio
10	No	Yes	Yes	High	Global	Audio
11	No	Yes	Yes	Low	Sequential	Audio
12	No	Yes	Yes	Low	Global	Audio
13	No	No	Yes	High	Sequential	Text
14	No	No	Yes	High	Global	Audio
15	No	No	Yes	Low	Sequential	Text
16	No	No	Yes	Low	Global	Audio
17	Yes	Yes	No	High	Sequential	Audio
18	Yes	Yes	No	High	Global	Audio
19	Yes	Yes	No	Low	Sequential	Audio
20	Yes	Yes	No	Low	Global	Audio
21	Yes	No	No	High	Sequential	Text, Video
22	Yes	No	No	High	Global	Text, Video, Image
23	Yes	No	No	Low	Sequential	Text
24	Yes	No	No	Low	Global	Text, Audio
25	No	Yes	No	High	Sequential	Audio
26	No	Yes	No	High	Global	Audio
27	No	Yes	No	Low	Sequential	Audio
28	No	Yes	No	Low	Global	Audio
29	No	No	No	High	Sequential	Text, Audio, Video
30	No	No	No	High	Global	Audio, Video
31	No	No	No	Low	Sequential	Text
32	No	No	No	Low	Global	Text

Our approach uses the classification and regression tree (CART) technique [8], which classifies learners based on the attributes of the learners' context (Luminosity, Mobility, Connectivity, Leaning style). This is done to explore the relationship between the learner's contexts and the learning object format opted for, in which the target variable is well-known. Then the result of the decision tree is transformed into a set of rules proceeding from the root to the leaf presented as an algorithm generated to deduce the learning object's format from the learning context (Figure 7). For example, if the level of luminosity is high, the three Learning Object formats ($text_1$, $image_2$, $audio_3$, $video_4$) are attributed by priority ranking, otherwise, the learner's mobility is measured and a LO is suggested using a suitable format for the current situation and so on.

Algorithm 1: Set of learning context rules imposed to deduce the best learning object

Inputs: L: Luminosity; M: Mobility; N: Noise; C: Connectivity; LS: Learning_Style

Variables: L, M, N, C: String; LS: String; CoursList[]: Table; i: Entier

Initializations: i <- 0

Output:
Get learning objects in a specific format from CoursList table

```
IF luminosity = "yes" THEN
        CoursList[i] <- getLeaningOjet("text", "image", "audio", "video")
        i <- i +1
ELSE
   IF mobility = "yes" THEN
        CoursList[i] <- getLearningObject ("audio")
        i <- i +1
   ELSE
      IF noise = "yes" AND LS == "global" THEN
           CoursList[i] <- getLeaningOjet("text","image")
             i <- i +1
      IF noise = "yes" AND LS == "sequential" THEN
           CoursList[i] <- getLeaningOjet("text")
             i <- i +1
      ELSE
         IF Conectivity = "high" AND LS = "global" THEN
           CoursList[i] <- getLeaningOjet("audio", "video")
             i <- i +1
         ELSE IF Conectivity = "high" AND LS = "sequential"
             CoursList[i] <- getLeaningOjet("text", "audio", "Video")
             i <- i +1

         ELSE IF Conectivity = "low" AND LS = "global"
             CoursList[i] <- getLeaningOjet("text", "audio")
             i <- i +1
         ELSE IF Conectivity == "low" AND LS = "sequential"
             CoursList[i] = getLeaningOjet("text")
              i <- i +1
         ENDIF
      ENDIF
   ENDIF
ENDIF
Return CoursList
```

Fig. 7. Set of learning context rules procedure imposed to deduce the best learning object

5 Dataset

IAV HASSAN II provided the dataset used in this research. Four agronomy courses offered in the winter sessions of 2019, 2020, and 2021 constituted the data, which was gathered using the learning management system (LMS) Moodle. There were video editorials, interactive forums quizzes, and course materials included in the 16-week program. A total of 714 students were registered in these classes and some 127,524 events were produced.

6 Results and discussion

Once the optimal value of k [3] is determined for the global and sequential learning styles, the k-means clustering algorithm is applied to group the learners. Hence, the learners are split into four groups based on their degree preferences (very weak (Cr1), weak (Cr2), mild (Cr3), and strong (Cr4)). The feature values for the global and sequential learning styles are listed in Tables 9 and 10.

The behavior of each cluster is expressed through the feature values. As shown in Table 9, Cr1 and Cr2 have a lower value than the others. They have a very large number of learners, with 72% of the total number of learners. They are very low learning style preference clusters for the global learning style. However, the value of Cr3 is moderate compared to other clusters.

Table 9. Global learning style clusters preferences

Features (Mean)/Clusters	Cr1	Cr2	Cr3	Cr4
#seq_goto	1.35	15.62	37.97	61.51
# seek_video	8.39	45.78	120.23	234.81
#mean_global_navig	0.14	0.24	5.12	19.72
#progesss	1.97	12.42	1.14	2.17
#outline_visit	5.62	40.27	53.26	53.71
# of learners	**366**	**170**	**110**	**94**
% of learners	**50**	**22.97**	**14.86**	**12.70**
Cluster ls preferences	**Very low**	**Low**	**Moderate**	**High**

For both global and sequential learning styles (Tables 9 and 10), the students with low preferences represent a major portion of the corresponding clusters (22.97% and 28.37% learners respectively). The number of learners of all clusters with very high preferences for both global and sequential learning styles is low. This is due to the large number of learners that have dropped out of courses. However, the number of learners with low preference clusters is moderate with lower feature mean values for both types of learning styles.

Table 10. Sequential learning style clusters preferences

Features (Mean)/Clusters	Cr1	Cr2	Cr3	Cr4
# seq_next	0.89	8.81	32.67	91.13
# seq_prev	0.61	3.67	12.81	28.82
#mean_sequential_navig	0.27	1.22	1.63	1.02
# dist_unit_visit	1.75	8.73	41.62	81.71
# page_close	4.73	27.61	18.52	312.41
# of learners	**390**	**210**	**88**	**52**
% of learners	**52.70**	**28.37**	**11.89**	**7.02**
Cluster ls preferences	**Very low**	**Low**	**Moderate**	**High**

To assess the quality of the unsupervised approach, the Calinski-Harabasz index [42], which addresses the separation among clusters and the similarity of inter-clusters, was used. In Table 11, the index validation value for global and sequential learning styles are compared across different clustering algorithms. As a result, the k-means algorithm [37] is considered the best due to its maximum value compared to the other algorithms. Furthermore, moderate preferences for both learning styles revealed that the number of learners making up the cluster of global learning styles (14.86%) is slightly higher than those making up the cluster of sequential learning styles (11.89%).

Table 11. Internal assessment measures of clustering

Quality Index	Agglomerative	MiniBatch	Birch	K-means
Global learning style (Calinski_ harabaz index)	13079.15	14128.13	124107	**14239.11**
Sequential learning style (Calinski_ harabaz index)	3435.24	9432	4720	**5463.30**

At a later stage, we used the labeled dataset received after balancing the learning styles, then 4 classification algorithms were trained and compared on the basis of their prediction ability to select the best one. By analyzing the accuracy results of each model listed in Table 12, the DT model is selected for its highest accuracy value of 97%, which reflects its best performance. This constitutes an answer to our first research question.

Table 12. Prediction models (the best ones are marked in bold)

Algorithm	f1-Score	Accuracy	Recall	Precision
KNN	0.74	0.741	0.74	0.74
RF	0.96	0.962	0.96	0.96
NN	0.95	0.954	0.95	0.95
DT	**0.97**	**0.973**	**0.97**	**0.97**

For the second research question, several studies have been carried out on the recommendation of learning objects using context and learning style [20], [21]. As a result, the findings of our research (section 4.3) confirmed that context is a priority compared to the learning style for the adaptation and recommendation process. The learning style has a remarkable effect only when the contextual attributes have optimal values (Luminosity = Yes, Mobility = No, Noise = No, Connectivity = High). Given that the learner has a global learning style and that he is exposed to a high level of noise and low connectivity, the system must recommend learning objects in a format other than that appropriate to the learner's learning style. This process can assure that the learner benefits as much as possible from the learning object, and in a similar way to what he/she expected.

To assess our approach, the recommendation system computes the utility of the recommended resources differently [4]. LS_score is a utility score used in our approach to rank resources in the final recommendation list. Then, learners who completed their courses are asked to provide their assessments about the recommendations they have received. Based on their feedback and LS_scores, the Average Reciprocal Hit Rank (ARHR) scores are generated for the set of recommendations offered to learners [43]. ARHR was used as a non-normalized metric to assess the usefulness of LS_scores. ARHR scores range between 0 and 1.

ARHR is expressed by the following formula: $\frac{1}{N}\sum_{i=1}^{k} r_i$

Let N be the total number of recommended resources and K the number of resources valued by learners using a rating r_x. Given that for each completed recommendation, the h position is attributed with a 1/h utility. Two kinds of valuations have been studied; the first one is intended for the recommendation approach without context, while the second is devoted to the context-aware recommendation (Figure 8). As shown in Figure 7, the ARHR scores for the rankings of each context-free recommendation are shown in yellow while the context-aware recommendations are expressed in light blue.

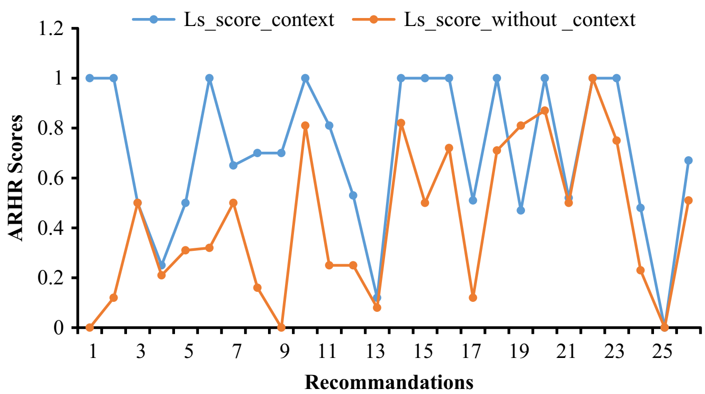

Fig. 8. ARHR measures for learning object recommendations

As shown in Figure 9, the mean ARHR calculated for the first one is 0.425, the equivalence of 42.5% of the useful recommendations for the learners, which is more a way to their expectations, while the second has a high mean score of 70.8%, which proved the effectiveness of the proposed approach.

The mean ARHR score is calculated by using the following formula:

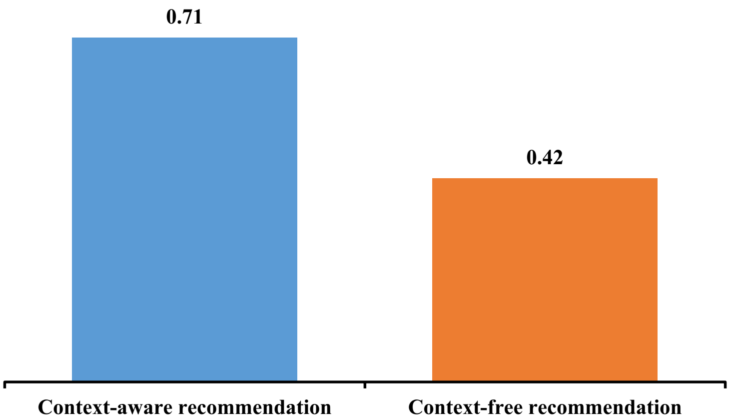

Fig. 9. Mean ARHR score for each recommendation learning type

In the future, it is intended to use the semantic data [44] of the resources scanned together with the learning object formats for a more granular recommendation of resources that provide good support for the learners. The use of deep learning in our recommendation system is substantial potential, as it is well developed and can handle a huge dataset and be automatically self-learned. It is also envisaged to integrate this approach into the MOOC environment to support a larger community of learners using a wide range of data.

7 Conclusion & future work

This study addressed the issue of identifying learners' sequential/global learning styles from their interactions with the LMS platform and recommending the right learning items according to learners' learning styles and context. The research we carried out takes into account contextual information and learning traces.

We used two types of experiments: firstly, an unsupervised clustering technique that was used to group learners according to their preferences for the understanding dimension of Felder and Silverman's learning styles model. Then, a new labeled dataset is built across the two learning styles balanced and measuring the dominance of each one. To design a learning style prediction model, 4 supervised classification algorithms were compared and these are Neural network (NN), K-nearest neighbors (KNN), Random Forest (RF), and decision tree (DT). The DT was preferred for its high accuracy (94%) in identifying the learning style. In the second experiment, our approach of a learning resource recommendation system is introduced using the frequency of learning objects of the identified learning style (LS_score) to select the right learning resources according to the learners' learning style. Then a contextual features vector is considered upon which the decision tree model is formed for adaptive rules used by this system to provide the relevant resources according to the learner's profile at the right time in the best way. The traces of 714 learners who signed up for one of the LMS courses delivered at IAV HASSAN II in the winter of 2019, 2020, and 2021 were examined and tested to validate the approach. The results of this research indicate that most learners prefer the global learning style and various contextual features such as high luminosity, low mobility, high connectivity, and normal noise level.

In future work, we expect to examine other dimensions of FSLSM. Furthermore, we will use the findings to build a recommendation system for learning resources and activities tailored to diverse learners' learning styles in LMSs.

8 Acknowledgment

I am grateful to the Hassan II Institute of Agronomy and Veterinary Medicine for its extensive support. I also wish to express my thanks to Mustapha NAIMI, Professor at the Hassan II Institute of Agronomy and Veterinary Medicine and Mr. Abderrahman EL HADDI, CTO and Founder of Enduradata Corporation, for their valuable comments and suggestions.

9 References

[1] K. Benabbes, B. Hmedna, K. Housni, A. Zellou, and A. El Mezouary, "New Automatic Hybrid Approach for Tracking Learner Comprehension Progress in the LMS," *Int. J. Interact. Mob. Technol.*, vol. 16, no. 19, pp. 61–80, 2022, https://doi.org/10.3991/ijim.v16i19.33733

[2] M. M. Tamada, R. Giusti, and J. F. de M. Netto, "Predicting Students at Risk of Dropout in Technical Course Using LMS Logs," *Electronics*, vol. 11, no. 3, p. 468, 2022, https://doi.org/10.3390/electronics11030468

[3] B. Hmedna, A. El Mezouary, and O. Baz, "A Predictive Model for the Identification of Learning Styles in MOOC Environments," *Cluster Comput*, vol. 23, no. 2, pp. 1303–1328, 2020, https://doi.org/10.1007/s10586-019-02992-4

[4] V. Thongchotchat, K. Sato, and H. Suto, "Recommender System Utilizing Learning Style: Systematic Literature Review," in *2021 6th International Conference on Business and Industrial Research (ICBIR)*, Bangkok, Thailand, May 2021, pp. 184–187, https://doi.org/10.1109/ICBIR52339.2021.9465832

[5] S. Rajper, N. A. Shaikh, Z. A. Shaikh, and G. Ali Mallah, "Automatic Detection of Learning Styles on Learning Management Systems using Data Mining Technique," *Indian Journal of Science and Technology*, vol. 9, no. 15, 2016, https://doi.org/10.17485/ijst/2016/v9i15/85959

[6] G. Ünsal, "A Study on the Importance of Learning Styles in Foreign Language Teaching," *ijlet*, vol. 6, no. 2, pp. 184–191, 2018, https://doi.org/10.18298/ijlet.3024

[7] O. S. Adewale et al., "Design of a Personalised Adaptive Ubiquitous Learning System," *Interactive Learning Environments*, pp. 1–21, 2022, https://doi.org/10.1080/10494820.2022.2084114

[8] D. Nawara and R. Kashef, "Context-Aware Recommendation Systems in the IoT Environment (IoT-CARS) – A Comprehensive Overview," *IEEE Access*, vol. 9, pp. 144270–144284, 2021, https://doi.org/10.1109/ACCESS.2021.3122098
[9] R. M. Felder, "Learning and Teaching Styles In Engineering Education," p. 11, 1988.
[10] A. Mumford and P. Honey, "Questions and Answers on Learning Styles Questionnaire," *Industrial and Commercial Training*, vol. 24, no. 7, 1992, https://doi.org/10.1108/00197859210015426
[11] A. Oweini and C. Daouk, "Effects of the Dunn and Dunn Learning Styles Model on Reading Comprehension and Motivation: A Case Study in Innovative Learning," p. 8, 2016.
[12] L. Willcoxson and M. Prosser, "Kolb's Learning Style Inventory (1985): Review and Further Study of Validity and Reliability," *British Journal of Educational Psychology*, vol. 66, no. 2, pp. 247–257, 1996, https://doi.org/10.1111/j.2044-8279.1996.tb01193.x
[13] N. Fleming, "Learning Styles Again: Varking up the Right Tree!," p. 3, 2006.
[14] R. M. Felder and B. A. Soloman, "Learning Styles and Strategies," (2000).
[15] J. Lo and P. Shu, "Identification of Learning Styles Online by Observing Learners' Browsing Behaviour Through a Neural Network," *British Journal of Educational Technology*, vol. 36, no. 1, pp. 43–55, 2005, https://doi.org/10.1111/j.1467-8535.2005.00437.x
[16] J. Schreurs, R. Dalle, and G. N. Sammour, "Authoring Systems Delivering Reusable Learning Objects," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 4, pp. 37–42, 2009, https://doi.org/10.3991/ijet.v4s2.812
[17] U. Javed, K. Shaukat, I. A. Hameed, F. Iqbal, T. Mahboob Alam, and S. Luo, "A Review of Content-Based and Context-Based Recommendation Systems," *Int. J. Emerg. Technol. Learn.*, vol. 16, no. 03, p. 274, 2021, https://doi.org/10.3991/ijet.v16i03.18851
[18] Y. El Borji and E. El Haji, "SG-LOM as Metadata Description for Serious Games to Benefit from LMS Monitoring Features," *Int. J. Emerg. Technol. Learn.*, vol. 17, no. 09, pp. 257–272, 2022, https://doi.org/10.3991/ijet.v17i09.29503
[19] P. Rodríguez, N. Duque, and D. A. Ovalle, "Multi-Agent System for Knowledge-Based Recommendation of Learning Objects Using Metadata Clustering," in *Highlights of Practical Applications of Agents, Multi-Agent Systems, and Sustainability – The PAAMS Collection*, vol. 524, J. Bajo, K. Hallenborg, P. Pawlewski, V. Botti, N. Sánchez-Pi, N. D. Duque Méndez, F. Lopes, and V. Julian, Eds. Cham: Springer International Publishing, 2015, pp. 356–364, https://doi.org/10.1007/978-3-319-19033-4_31
[20] I. El Guabassi, M. Al Achhab, I. Jellouli, and B. E. EL Mohajir, "Context-Aware Recommender Systems for Learning," *International Journal of Information Science and Technology*, pp. 17–25, 2018, https://doi.org/10.57675/IMIST.PRSM/IJIST-V1I1.11
[21] A. Livne, E. S. Tov, A. Solomon, A. Elyasaf, B. Shapira, and L. Rokach, "Evolving Context-Aware Recommender Systems With Users in Mind," 2020, https://doi.org/10.48550/ARXIV.2007.15409
[22] K. Benabbes, K. Housni, A. E. Mezouary, and A. Zellou, "Recommendation System Issues, Approaches and Challenges Based on User Reviews," *JWE*, 2022, https://doi.org/10.13052/jwe1540-9589.2143
[23] M. Casillo, F. Colace, M. De Santo, A. Lorusso, R. Mosca, and D. Santaniello, "VIOT_Lab: A Virtual Remote Laboratory for Internet of Things Based on ThingsBoard Platform," in *2021 IEEE Frontiers in Education Conference (FIE)*, Lincoln, NE, USA, Oct. 2021, pp. 1–6, https://doi.org/10.1109/FIE49875.2021.9637317
[24] R. Vankayalapati, K. B. Ghutugade, R. Vannapuram, and B. P. S. Prasanna, "K-Means Algorithm for Clustering of Learners Performance Levels Using Machine Learning Techniques," *RIA*, vol. 35, no. 1, Art. no. 1, 2021, https://doi.org/10.18280/ria.350112
[25] D. Müllner, "Modern Hierarchical, Agglomerative Clustering Algorithms," 2011, https://doi.org/10.48550/ARXIV.1109.2378

[26] R. Vankayalapati, K. B. Ghutugade, R. Vannapuram, and B. P. S. Prasanna, "K-Means Algorithm for Clustering of Learners Performance Levels Using Machine Learning Techniques," *RIA*, vol. 35, no. 1, pp. 99–104, 2021, https://doi.org/10.18280/ria.350112

[27] J. Sander, M. Ester, H.-P. Kriegel, and X. Xu, "Density-Based Clustering in Spatial Databases: The Algorithm GDBSCAN and Its Applications," *Data Mining and Knowledge Discovery*, vol. 2, no. 2, pp. 169–194, 1998, https://doi.org/10.1023/A:1009745219419

[28] T. Zhang, R. Ramakrishnan, and M. Livny, "BIRCH: An Efficient Data Clustering Method for Very Large Databases," *SIGMOD Rec.*, vol. 25, no. 2, pp. 103–114, 1996, https://doi.org/10.1145/235968.233324

[29] F. Khan, "An Initial Seed Selection Algorithm for k-means Clustering of Georeferenced Data to Improve Replicability of Cluster Assignments for Mapping Application," *Applied Soft Computing*, vol. 12, no. 11, pp. 3698–3700, 2012, https://doi.org/10.1016/j.asoc.2012.07.021

[30] Y. Choi and J. Kim, "Learning Analytics for Diagnosing Cognitive Load in E-Learning Using Bayesian Network Analysis," *Sustainability*, vol. 13, no. 18, p. 10149, 2021, https://doi.org/10.3390/su131810149

[31] H. R. D. AL-Fayyadh, S. A. Ganim Ali, and Dr. B. Abood, "Modelling an Adaptive Learning System Using Artificial Intelligence," *WEB*, vol. 19, no. 1, pp. 01–18, 2021, https://doi.org/10.14704/WEB/V19I1/WEB19001

[32] A. Klašnja-Milićević, B. Vesin, M. Ivanović, and Z. Budimac, "E-Learning Personalization Based on Hybrid Recommendation Strategy and Learning Style Identification," *Computers & Education*, vol. 56, no. 3, pp. 885–899, 2011, https://doi.org/10.1016/j.compedu.2010.11.001

[33] J. Bernard, T.-W. Chang, E. Popescu, and S. Graf, "Learning Style Identifier: Improving the Precision of Learning Style Identification Through Computational Intelligence Algorithms," *Expert Systems with Applications*, vol. 75, pp. 94–108, 2017, https://doi.org/10.1016/j.eswa.2017.01.021

[34] A. E. Mezouary and B. Hmedna, "An Unsupervised Method for Discovering How Does Learners Progress toward Understanding in MOOCs," *IJITEE*, vol. 10, no. 5, pp. 40–49, 2021, https://doi.org/10.35940/ijitee.E8673.0310521

[35] P. García, A. Amandi, S. Schiaffino, and M. Campo, "Evaluating Bayesian Networks' Precision for Detecting Students' Learning Styles," *Computers & Education*, vol. 49, no. 3, pp. 794–808, 2007, https://doi.org/10.1016/j.compedu.2005.11.017

[36] K. Adil, E. Amrani, and O. Lahcen, "Modeling and Implementing Ontology for Managing Learners' Profiles," *IJACSA*, vol. 8, no. 8, Art. no. 8, 2017, https://doi.org/10.14569/IJACSA.2017.080819

[37] E. Umargono, J. E. Suseno, and V. G. S. K., "K-Means Clustering Optimization using the Elbow Method and Early Centroid Determination Based-on Mean and Median," in *Proceedings of the International Conferences on Information System and Technology*, Yogyakarta, Indonesia, 2019, pp. 234–240, https://doi.org/10.5220/0009908402340240

[38] J. Gope and S. Kumar Jain, "A Learning Styles Based Recommender System Prototype for edX Courses," in *2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, Bangalore, Aug. 2017, pp. 414–419, https://doi.org/10.1109/SmartTechCon.2017.8358407

[39] Z. Brahmia, S. Brahmia, F. Grandi, and R. Bouaziz, "JUpdate: A JSON Update Language," *Electronics*, vol. 11, no. 4, p. 508, 2022, https://doi.org/10.3390/electronics11040508

[40] A. Agocs and J.-M. L. Goff, "A Web Service Based on RESTful API and JSON Schema/JSON Meta Schema to Construct Knowledge Graphs," in *2018 International Conference on Computer, Information and Telecommunication Systems (CITS)*, Alsace, Colmar, France, Jul. 2018, pp. 1–5, https://doi.org/10.1109/CITS.2018.8440193

[41] R. A. W. Tortorella and S. Graf, "Considering Learning Styles and Context-Awareness for Mobile Adaptive Learning," *Educ Inf Technol*, vol. 22, no. 1, pp. 297–315, 2017, https://doi.org/10.1007/s10639-015-9445-x
[42] H. Jeon, M. Aupetit, D. Shin, A. Cho, S. Park, and J. Seo, "Sanity Check for External Clustering Validation Benchmarks using Internal Validation Measures," 2022, https://doi.org/10.48550/ARXIV.2209.10042
[43] C. T. Hoyt, M. Berrendorf, M. Galkin, V. Tresp, and B. M. Gyori, "A Unified Framework for Rank-Based Evaluation Metrics for Link Prediction in Knowledge Graphs," 2022, https://doi.org/10.48550/ARXIV.2203.07544
[44] N. Idrissi and A. Zellou, "A Systematic Literature Review of Sparsity Issues in Recommender Systems," Soc. Netw. Anal. Min., vol. 10, no. 1, p. 15, 2020, https://doi.org/10.1007/s13278-020-0626-2

10 Authors

Khalid Benabbes is a PhD student at the MISC Laboratory, Faculty of Sciences, Ibn Tofail University, Kénitra, Morocco. He is currently a software engineer at the Hassan II Institute of Agronomy & Veterinary Medicine in Rabat. He holds an engineering degree in Computer Sciences from ENSA, Agadir. His research interests includes MOOC, Recommender systems, Machine Learning, and Data Science.

Housni Khalid received his PhD in Computer Sciences from the University of Ibn Zohr Agadir, Morocco. In 2014, he joined the Department of Computer Sciences, Faculty of Sciences, Ibn Tofail University, Kénitra, Morocco. His research interests includes image/video processing and networks reliability. E-mail: housni.khalid@uit.ac.ma

Zellou Ahmed received his PhD in Computer Sciences from Mohammedia School of Engineering, Rabat, Morocco. He is currently a professor at the National School of Computer Sciences and Systems Analysis (ENSIAS). His research interests includes Information Integration, Hybrid, Semantic and Fuzzy, Content Integration, Semantic P2P, Cloud Integration. E-mail: ahmed.zellou@um5.ac.ma

Brahim Hmedna Received his PhD in Computer Sciences from the University of Ibn Zohr Agadir, Morocco. He is currently an Assistant Professor at the National School of Business and Management in Agadir. His research interests includes MOOC, Learning Styles, Machine Learning and Data Science. E-mail: brahim.hmedna@edu.uiz.ac.ma

Ali El Mezouary received his PhD in Computer Sciences from the University of Ibn Zohr, Agadir, Morocco. He is a full professor at ESTA, University of Ibn Zohr. His research interests includes Web Semantic and Adaptive Learning Systems. E-mail: a.elmezouary@uiz.ac.ma

Article submitted 2023-01-26. Resubmitted 2023-02-28. Final acceptance 2023-03-01. Final version published as submitted by the authors.