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PAPER

Toward a Context-Aware Course-Planning Model in Pervasive Learning Environments

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ABSTRACT

This article proposes a context-aware course-planning model for pervasive learning environments. The model considers learners' preferences, including their learning styles, locations, activities, and devices. The model generates four-dimensional contexts based on these preferences, each dimension being a weighted vector of visual, aural, read/write, and kinesthetic (VARK) features. Using a content-based similarity algorithm, the model adapts the course content to each learner's context. The courses are created in a sequence of rings, each containing all possible learning materials (LMs) that have the same content in different formats. Each LM is represented by a vector with weights like those of the learners' context dimensions. The model generates all possible plans based on the predefined contexts of the learner, detects the learner's actual context, and adapts the content accordingly. The goal of the model is to enable learners to learn what they want, in the way they prefer, and to complete courses efficiently, at any time, place, and during any activity, in the appropriate format.

KEYWORDS

pervasive learning, adaptive learning, context-aware, learning styles, content-based filtering

1 INTRODUCTION

With rapid developments in technology (especially ubiquitous computing) and educational theory [1], digital learning—including ubiquitous learning, also known as pervasive learning (u-learning, p-learning)—has become an important trend in the revolution of electronic learning (e-learning) [2] and the most efficient learning and teaching technique adopted across the world [3]. p-learning allows learners to learn at any time and in any location.

Context-aware systems and context-aware recommendation systems [4] have harmonization with environmental components. A system is considered context-aware if it uses context information to give relevant information to the user [5]. *Context* is any information used to characterize an entity's situation. In pervasive

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learning, context can be information about a learner (personal information, preferences, interests, etc.), places (locations), time (time of the day, availability, task duration, etc.), device (smartphone, tablet, laptop, etc.), or physical environment (noise level, illumination level, weather condition, etc.) [6], [7].

We can define a learner's learning style by the preferential way in which the learner receives and processes the learning activity. The learner's learning preferences can be determined by the results in terms of performance, motivation, and satisfaction [8]. Many researchers have used the Felder-Silverman learning style model (FSLSM), consisting of techniques that can be used to determine the preferences of the learner [3], [9], [10]. FSLSM categorized the learning preferences into different dimensions—mainly active and reflective learners, sensing and intuitive learners, visual and verbal learners, and sequential and global learners [11]. The VARK learning-style model introduced by Fleming includes a questionnaire that identifies a person's sensory modality preference in learning. This model classifies learners into four different learning modes; visual (V), aural (A), read/write (R), and Kinesthetic (K) [12], [13].

In a related area, *adaptation* is defined as "the ability to make appropriate responses to changed or changing circumstances" [14]. It can also be defined as an adjustment to a changed circumstance or environment. In the context of learning, authors in [15] define *adaptive learning systems* as "learning programs capable of adapting themselves to the individual abilities of the learner, e.g., previous knowledge, interests, weaknesses or preferences about forms of representation." [16]. The goal of adaptive e-learning is to deliver the right content, to the right person, at the proper time, in the most appropriate way—any time, any place, any path, any pace [17].

This paper presents the context-aware course-planning (CACP) model for use in pervasive learning environments. The CACP model consists of four modules that work together to provide learners with dynamically adaptive course content that is aligned with their contextual needs.

The first module is the System Initialization module, which characterizes the different contexts in which learners operate and evaluates the information collected using the VARK model. The second module is the Context Management module, which determines all possible contexts for learners. It calculates learners' contextual learning styles based on their preferences and represents their contexts as VARK vectors. The third module is the Course Management module, where the learning courses and materials that are aligned with the learners' contextual needs are created. These learning materials are represented as VARK vectors, with appropriate weights assigned by the course's designers. Finally, the fourth module is the Adaptation module, which delivers dynamically adaptive course content to learners based on their contextual learning styles. A cosine similarity algorithm is used for content-based filtering between each learner's predefined context and the set of the course's learning materials. The module suggests the best plans to follow for each context to complete the course. It also detects the learner's actual context and matches it with one of his predefined contexts.

The goal of the CACP model is to allow learners to learn what they want in the way they prefer and to complete courses efficiently, at any time and place, and during any activity, in the appropriate format.

This paper is structured into six sections. The following section examines the motivations for this work, and Section 3 provides a succinct overview of related work. Section 4 explains the proposed approach and outlines its components in detail. Section 5 evaluates the approach against the identified challenges. Finally, Section 6 presents our conclusions.

2 MOTIVATING SCENARIOS

Most learning management systems (LMSs), Massive Open Online Courses, and learning platforms, such as Moodle [18], Blackboard [19], and others, present courses to all learners in the same static manner. The teachers create their courses, and all enrolled learners follow the courses' contents in the same way. We can consider a course like a chain with a beginning and an end and sequenced as a set of rings, with each ring containing an LM (Figure 1).

In the proposed model, the teacher can create a course, but in different ways according to the learners' contexts, to allow learners to follow the same course but in different manners. The components of the course are not reordered; the learners follow the same order of the course in different ways based on their preferences. More precisely, each learner, before choosing a course, ought first to express a set of learning preferences. Accordingly, the system generates his/her eventual contexts and proposes the best plans for him/her. In this manner, all the learners follow the same content but in different formats. The learner finds himself freer and more comfortable. Moreover, the availability of a large variety of content allows the teacher to make the same course differently.

Fig. 1. Traditional course plan in LMSs and learning platforms

3 RELATED WORK

In recent years, context-aware adaptive learning has gained popularity in the field of education. In this type of learning, not only the content but also the environment, format, and devices must be adaptive. Several studies have been conducted on the topic of adaptive learning, emphasizing the importance of this field. Among them are many surveys, where [20] conducted a survey on 53 studies published between 2010 and 2018 on adaptive context-aware learning environments. A systematic mapping of the literature on AI-enabled adaptive learning systems was performed in [21], where 147 studies published between 2014 and 2020 were analyzed. [22] presented a systematic mapping review that focuses on context-aware analysis and its approach to learning processes in mobile learning (m-learning) and ubiquitous learning (u-learning). The following works will be classified based in common fields studied to gain a better understanding of the research area.

Studies on personalized and adaptive context-aware mobile learning: [3] studied personalized and adaptive context-aware mobile learning. [23] discussed the advancement and research trends of smart learning systems in pervasive environments. [24] analyzed a vast volume of published articles in the field of adaptive learning. [25] compiled the challenges faced by context-aware recommendation systems and demonstrated the ability of bio-inspired computing techniques and statistical computing techniques to handle these challenges. [26] presented a context-aware system that adapts the learning content based on the contexts of the user. Context awareness, such as the user's maturity, the cognitive load of the learner, and device configuration, was used to retrieve context data. Content adaptation, such as resource, device, and network adaptation, was accountable for suitable adaptation of the learning materials in the application. Additionally, the approach in [31], known as smart enhanced context-aware for flipped mobile learning, provides customized course content based on the context, particularly the mobile-device context, of the learners.

Studies based on learning styles: [27] proposed to identify the learning styles of the learner by capturing the learning behavior of the learner in the e-learning portal using Web Log Mining. The learning styles were then mapped to FSLSM categories, and each category was provided with contents and an interface suitable for that category. The Fuzzy C Means algorithm was used to cluster the captured learning behavioral data into FSLSM categories. [9] proposed a model called Dynamic Mobile Adaptive Learning Content and Format, which considers the learner's knowledge level and learning styles to provide suitable learning for every student. [28] proposed an approach to provide adaptation and personalization in ubiquitous settings, considering a combination of students' learning styles, existing learning standards, and learner context.

Studies using AI: [29] proposed myPTutor, a general and effective approach that uses AI planning techniques to create fully tailored learning routes, as sequences of learning objects that fit the pedagogical and students' requirements. This approach has the potential applicability to support e-learning personalization by producing and automatically solving a planning model based on e-learning standards in a vast number of real scenarios, from small to medium/large e-learning communities. The study in [30] presents a novel solution for personalizing learning using artificial neural network technology. The system aims to classify students' learning styles based on their metacognitive skills using the FSLSM. The automatic classification of learning style offers valuable insights about the student and helps in providing support, while the use of recent student data allows for real-time recognition of the learning style, providing a deeper understanding of the learning process. The authors found that this approach was promising compared with previous works.

Previous studies have proposed learning systems that are adapted to the learners' contexts, often using the FLSM learning style model to categorize learners based on their learning styles and provide appropriate content. However, our proposed approach is different by calculating learners' learning styles based on multiple components of their contexts, using the VARK learning-style model. This results in a more flexible and relative system, allowing for multiple possible plans with rich course content in various formats.

4 CACP: A CONTEXT-AWARE COURSE-PLANNING APPROACH

We propose an approach for adaptive pervasive learning using a content-based filtering algorithm for course planning. This approach enables learners and teachers to work together or independently throughout the learning process.

The proposed architecture consists of four main modules (see Figure 2): System Initialization, Course Management, Context Management, and Adaptation. Each module takes input data and produces output data. The modules are designed to work sequentially to provide a complete approach for pervasive learning adaptation.

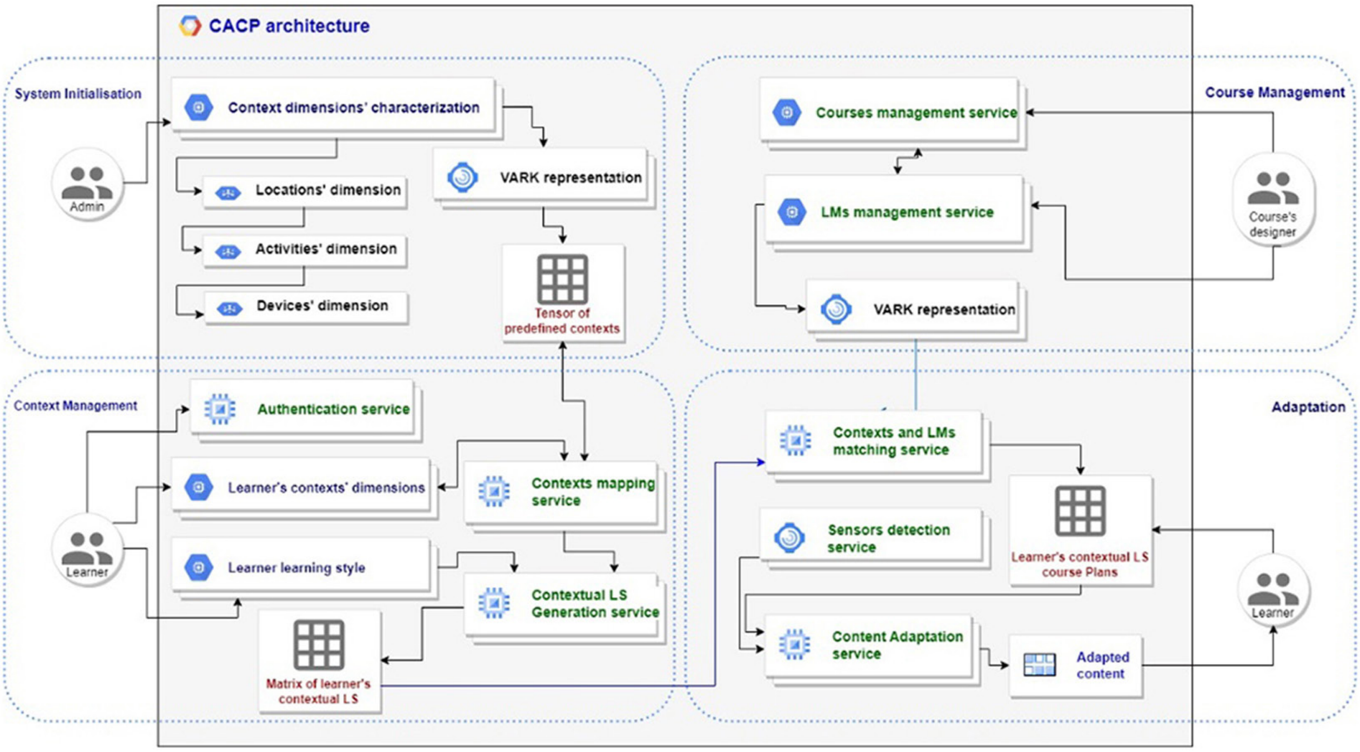

Fig. 2. Architecture of the proposed model

4.1 System initialization module

The aim of this module is to thoroughly characterize the different contexts in which learners operate, including their physical locations, daily activities, and the devices they use. This information will be evaluated using the VARK model, which assigns weights to each contextual component based on its perceived impact on the learner's learning experience.

The system administrator, who has expertise in the field, uses a tensor-based approach to comprehensively characterize the different contexts in which learners operate. This approach involves constructing a multi-dimensional tensor, where each combination of dimensions represents a contextual component, such as location, activity, and device, but can be extended to include other dimensions, such as time of day, environmental conditions, or social interactions. The tensor approach allows for a more flexible and scalable evaluation of the different contexts that learners may encounter, enabling the administrator to assign appropriate weights to each component.

While the VARK model is one popular approach for assigning weights, other learning-style models such as the Felder-Silverman [11] or Kolb [32] models can be used instead or in combination to enhance the customization of the learning experience. By using a tensor-based approach, the administrator can ensure a comprehensive and adaptable characterization of learners' contextual needs, leading to more effective and personalized course planning.

The System Initialization module is executed only once during the setup of the learning system. The administrator, as an expert, creates all potential items for each context dimension in the learning environment. The administrator assigns weights to each item, following the VARK model. Each item is represented by a VARK vector with four features, where the value of each feature is between 0 and 1.

As an example, we shall consider a multidimensional context tensor of four locations, five activities, and three devices. We consider the item Home in the Location dimension. The administrator can give its VARK weights as follows: Location_Home(1,1,0.4,0.6), which means that at Home all the LMs with visual and auditory formats are permitted, but read/write LMs are permitted with the percentage of 40% and Kinesthetic LMs with the percentage of 60%. The item Driving in the Activity dimension is weighted as follows Activity_Driving(0.25,1,0,0), which means that when driving, the visual LM format is allowed at 25%, the aural format is permitted, but the read/write and kinesthetic formats are not allowed. For devices, there are several methods to calculate the weight corresponding to each feature. The system can adopt the method used in [31]. This process is repeated for all items within each dimension, resulting in a comprehensive representation of the learner's context in the form of a tensor. Figure 3 provides a summary of the dimensions included in the tensor created in this example with their corresponding VARK weights. The tensor contains four locations: Home, Library, Park, and Coffee shop; five activities: Driving, Riding, Walking, Collaboration with others, and Cooking; and three devices: Smart_Phone, Laptop, and Tablet.

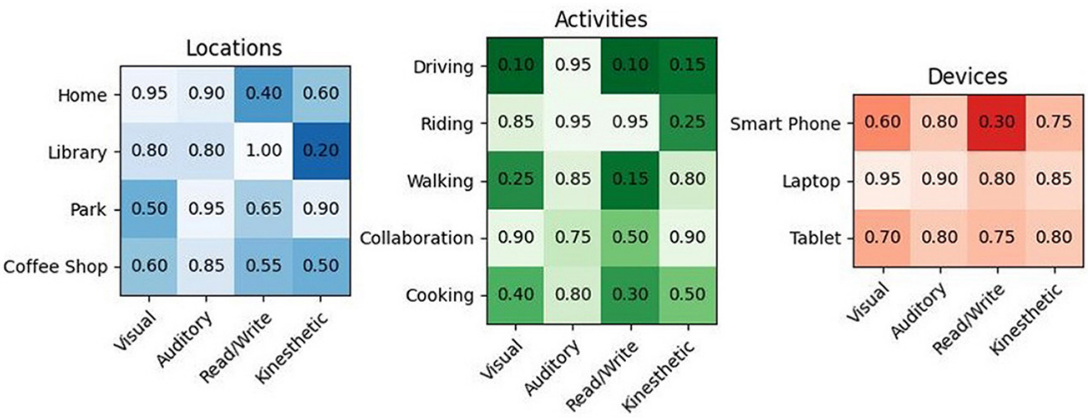

Fig. 3. Contexts dimensions' characterization

4.2 Context management module

The Context Management module plays a crucial role in generating learners' predefined contexts based on their preferences, including their learning styles, locations, activities, and devices. This module utilizes the information collected in the System Initialization module to determine all possible contexts for learners. The module includes various steps, such as calculating each learner's learning style based on his preferences and representing his contexts as VARK vectors, which are then used for further adaptation. Therefore, this module prepares the learners' contextual learning styles by processing the input received from the System Initialization module before passing it on to the Adaptation module.

The learner has to express his preferences. In other words, the learner defines his eventual learning contexts. This module is composed of the following services:

Authentication service: At this stage, if a learner does not have an account, he is treated as a visitor. He can access and explore the different themes and consult the available courses. If a visitor chooses one or more courses to learn and decides to become a learner, he has to create an account. This is done by providing the necessary information to be able to authenticate himself afterward.

Define learner's learning style: The learning style of each learner is considered as the fourth dimension of his learning context. Therefore, the learner gives weights for his learning style's VARK vector features. He does this operation only for the first time he chooses a course. If he selects other courses, he can validate his first choice or modify it. The weights should be between 0 and 1 for each feature. As an example, let's take Adam as a learner who has defined his learning style as follows: Adam_LS(0.8, 1, 0.3, 0.5). That is to say that Adam is visual at 80%, Auditory at 100%, Read/Write at 30%, and Kinesthetic at 50%.

Define learner's contexts dimensions: Afterwards, the learner has to choose from the tensor dimensions his learning locations, the activities in which he wants to learn, and finally the devices that he will use for the learning. The administrator, as described in the system initialization above, has already created the majority of potential locations, activities, and devices for learning. If the learner does not find one or more of these context dimension items, he can add them. It will be clear that the administrator must approve every dimension item the learner adds. If the administrator finds resemblances between items in the same dimensions, he can group them in the same class. For example, if a learner adds the item Running to the dimension Activity because he did not notice the item Walking or he considered them different, the administrator can group both activities together.

At this stage, all of the possible learning contexts for a learner have been defined based on his preferences. If the learner has selected n locations, m activities, and k devices, the maximum number of his learning contexts will be $(n \times m \times k)$. However, it's important to note that the learner can be in only one of these contexts at a time during his course learning.

Mapping VARK model features to learner's contexts dimensions: After the learner has selected his preferred locations, activities, and devices, the context-mapping service maps the different VARK model features to the corresponding context dimensions. This mapping is done automatically since the administrator has already assigned a weight (W) to each dimension item corresponding to the VARK model features, as explained in the System Initialization module. This ensures that the learner's defined contexts are accurately represented and used for the adaptation process. Table 1 displays the possible learning contexts for a learner based on his VARK learning style, location, activity, and device preferences. The first row shows the weights of VARK learning-style features. The next rows represent the locations (from 1 to n), activities (from 1 to m), and devices (from 1 to k) that a learner has selected. Each location, activity, and device has four columns that correspond to VARK features, denoted by the letters v, a, r, and k, respectively.

Table 1. Mapping VARK model features to learner's defined contexts dimensions

		Visual	Aural	Read/Write	Kinesthetic
Learning style		W_ls_v	W_ls_a	W_ls_r	W_ls_k
Location	Location_1	W_loc1_v	W_loc1_a	W_loc1_r	W_loc1_k
	……………	……	……	……	……
	Location_n	W_locn_v	W_locn_a	W_locn_r	W_locn_k
Activity	Activity_1	W_act1_v	W_act1_a	W_act1_r	W_act1_k
	……………	……	……	……	……
	Activity_m	W_actm_v	W_actm_a	W_actm_r	W_actm_k
Device	Device_1	W_dev1_v	W_dev1_a	W_dev1_r	W_dev1_k
	……………	……	……	……	……
	Device_k	W_devk_v	W_devk_a	W_devk_r	W_devk_k

Let's continue with our example and suppose that Adam has selected the following items for his learning contexts: Home and Park as locations, Collaboration with Others, Walking, and Riding as activities, and Smart_phone and Laptop as devices for learning. Figure 4 summarizes Adam predefined learning-contexts dimensions with their corresponding VARK weights.

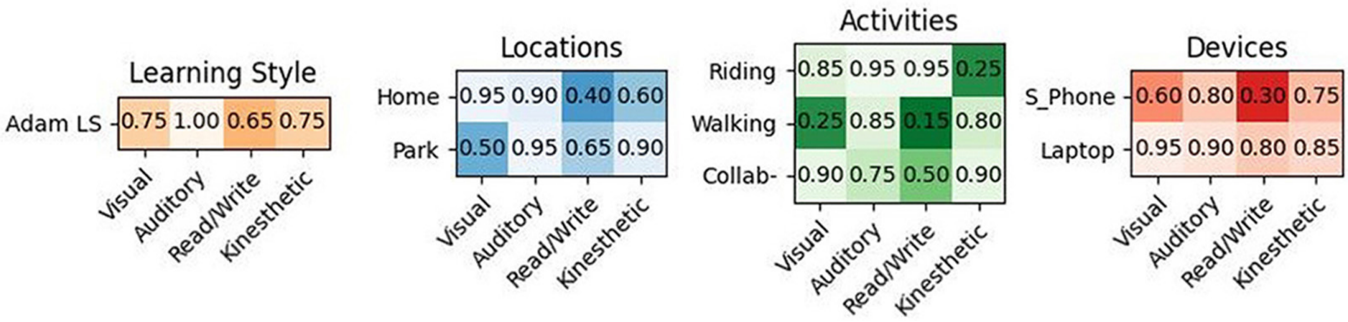

Fig. 4. Example of learning-contexts dimensions

Contextual learning-style generation: This step is one of the most important ones in our approach. As the context dimensions have been already defined in the System Initialization module and after mapping them to those selected by the learner based on his choice, the system will generate contextual learning-style contexts based on the learner's learning style. These M-generated contexts (where $M = n \times m \times k$) represent all possible combinations between the items of the four learner context dimensions (learning style, locations, activities, and devices), and they will also be represented by VARK vectors. Here, the module calculates the new weights of VARK features of each generated context, starting from the dimension vectors resulting from the previous service. Consequently, as shown in Table 2, a labeled vector also represents every generated context_i ($1 \leq i \leq M$), which will be the result of the intersection of the vector dimensions that compose each context.

Table 2. Calculating the new VARK weights of the generated contexts

Context_i	Visual	Aural	Read/Write	Kinesthetic
Learning style	W_ls_v	W_ls_a	W_ls_r	W_ls_k
Location_x (1≤x≤n)	W_loc_v	W_loc_a	W_loc_r	W_loc_k
Activity_y (1≤y≤m)	W_act_v	W_act_a	W_act_r	W_act_k
Device_z (1≤z≤k)	W_dev_v	W_dev_a	W_dev_r	W_dev_k
Context_i (1≤i≤M)	W_ls_v∩W_loc_v∩W_act_v∩W_dev_v	W_ls_a∩W_loc_a∩W_act_a∩W_dev_a	W_ls_r∩W_loc_r∩W_act_r∩W_dev_r	W_ls_k∩W_loc_k∩W_act_k∩W_dev_k

Each generated context will take the minimum weight between the weights of its dimensions for every VARK feature. These steps are shown in the following algorithm.

```
import numpy as np
# Define the dimensions of the learner tensor
n_locations = n
n_activities = m
n_devices = k

# Define the component vectors with VARK
learning_style_vector = [W_ls_v, W_ls_a, W_ls_r, W_ls_k]
```

```
  location_vectors =
fetch_locations(System_Initialisation_locations_items)
  activity_vectors =
fetch_activities(System_Initialisation_activities_items)
  device_vectors =
fetch_devices(System_Initialisation_devices_items)

  # Create the learner tensor
  learner_context_tensor = np.zeros(
    (1, n_locations, n_activities, n_devices, 4))

  # Calculate the minimum VARK weights for each component and
fill the tensor
  component_mins = np.minimum.reduce(
    [learning_style_vector, location_vectors,
activity_vectors, device_vectors])
  learner_context_tensor[:] = component_mins.reshape(
    (1, n_locations, n_activities, n_devices, 4))
```

The output of the algorithm is an (M,4) matrix representing M contextual learning styles for each learner, with four VARK columns.

If we apply this algorithm to generate Adam's contextual learning-style contexts, we will use the information he provided regarding his two preferred locations, three activities, and two devices. The system will create all possible combinations between these dimensions, resulting in a total of 12 contexts. Figure 5 visualizes all of Adam's contextual learning-style contexts, representing each context and its corresponding VARK weights. This figure provides a quick overview of all possible learning situations for Adam, helping him and his instructors expect the most suitable learning plans for each context.

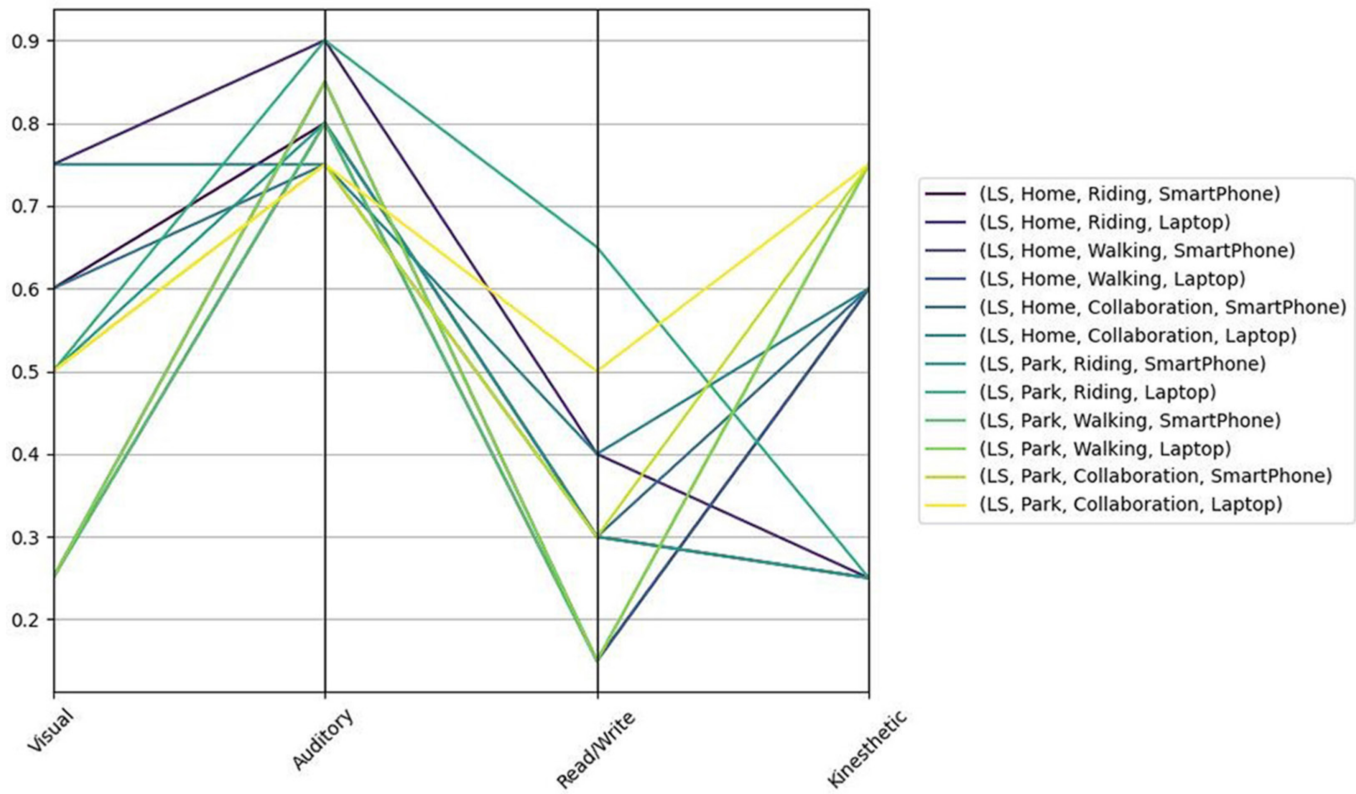

Fig. 5. Contextual learning-style generation approach for each learner

4.3 Course Management module

The Course-Management module comprises two main services: Course Management service and Learning Materials Management service. Courses designers create learning courses and materials that are aligned with the learners' contextual needs. These learning materials are represented as VARK vectors, with the appropriate weights.

Courses management service: A course is a finite sequence of rings or units that has a defined beginning and end (see Figure 1). The course designer creates the course sequence and can update or remove rings at any time. Once the course sequence is created, the designer must assign the corresponding LMs from the LMs repository to each ring. All LMs belonging to the same ring represent the same content but in different formats. Once the course designer completes the course creation and determines that it is ready to be published and visible to learners, he can add it to the courses' list. The course designer can modify or update the course at any time, or remove it completely.

Learning materials management service: Learning materials (LMs) also known as learning objects (LOs) are small, reusable components, video demonstrations, tutorials, procedures, stories, assessments, simulations, or case studies. However, rather than use them to build castles, they are used to build larger collections of learning materials [17].

A course is composed of a set of LMs linked one after the other. Each LM can be in a single format or several formats but with percentages. Therefore, we represent any LM by a vector of four features of the VARK model in the same way we have done with context dimensions. In this context, a course designer, when he creates LMs for his course or reuses those that exist in the LMs repository, must also give the percentage of each format by filling in the weights of the VARK vector features.

As an example, let's take the course Overview on Algorithms. It is composed of the following five rings: Introduction, Variables, Conditionals, Functions, and Recursion. For instance, if an MP3 file in Ring 3 (Conditionals) is used as a learning material, it will be represented as LM_3_1(0,1,0.2,0.4). Similarly, a PDF file will be represented as LM_3_2(0.25,0,1,0.3). It should be noted that the weights assigned by the course designers to each LM are based on their content format rather than their file type.

4.4 Adaptation module

The Adaptation module is the final component of our proposed approach. It plays a role in delivering dynamically adaptive course content to learners, based on their current context. This module leverages the use of three services, the Contexts and LMs Matching service, the Sensors Detection service, and the Content Adaptation service.

Contexts and LMs matching service: This service is the core of the proposed approach. We have determined that the maximum number of learning-generated contexts for each learner is M (where $M = n \times m \times k$). We assume that each learner can be placed in one of his predefined contexts during each phase (ring) of the learning course. To ensure that the appropriate learning materials are displayed for each context and stage, we utilize the cosine similarity algorithm to compare each context with each learning material in the set corresponding to the relevant ring.

Through this process, the service identifies the most suitable learning materials for each context and each stage of the course. Essentially, this service facilitates course content adaptation to the learner's individual contexts.

The cosine similarity between each Context_i vector in the set of M contexts, and an LM_n_t vector (n is the number of the ring in the course, and t is the number of the LM in the ring n) is defined by equation (1):

$$COS(Context_i,\ LM_t^n) = \frac{Context_i * LM_t^n}{\|Context_i\|\,\|LM_t^n\|} \tag{1}$$

We repeat this process as many times as the number of rings of the course, as shown in the following algorithm.

Fetch the matrix X_C of size (M, 4), where each row of X_C represents a context VARK vector in the set of M contexts

For each ring n in the course chain:

1. Create a matrix X_LM of size (m, 4), where m is the number of LMs in the ring n, and each row of X_LM represents an LM VARK vector in the ring n
2. Compute the dot product between X_LM and X_C using matrix multiplication, resulting in a matrix of size (m, M) containing the dot products for each LM-context pair
3. Compute the magnitudes of X_LM and X_C using the square root of the sum of squares of each element in the matrix, resulting in two matrices of size (m, 1) and (M, 1) containing the magnitudes for each LM and each context
4. Compute the product of the magnitudes of X_LM and X_C, resulting in a matrix of size (m, M) containing the product for each LM-context pair
5. Compute the cosine similarity scores as the element-wise division of the dot product and the product of magnitudes, resulting in a matrix of size (m, M) containing the cosine similarity scores for each LM-context pair
6. For each context i in the set of M contexts:

   a. Extract the i-th column of the cosine similarity matrix, resulting in a vector of size (m, 1) containing the cosine similarity scores for each LM with respect to the i-th context

   b. Sort the vector of cosine similarity scores in descending order, resulting in a sorted vector of size (m, 1) containing the cosine similarity scores for each LM with respect to the i-th context

   c. Store the sorted LM matrix for the i-th context

7. Return the set of sorted LM matrices for all contexts in the set of M contexts

To ensure efficient processing and minimize computation time during the learning operation, we perform the computation of the sorted LMs for each ring according to each context prior to the start of the course. This allows us to pre-select the appropriate learning materials for each context and ring, and avoid the need for real-time computation of the current context and its associated learning materials. By doing so, we can simply select the relevant context from those already predefined, rather than performing additional computations during the learning process. As a result of this pre-computation, the set of possible plans or paths for a learner with M contexts and a course composed of N rings will contain at most M^N possible plans.

In Figure 6, we provide an example of the situation described above, which displays the appropriate learning materials for each context and ring. Only the LM with high score in each context will be displayed. The Contexts and LMs Matching service allows learners to see how they will progress through the chosen course. This gives learners a clear understanding of their learning path and enables them to make informed decisions about their approach to the course.

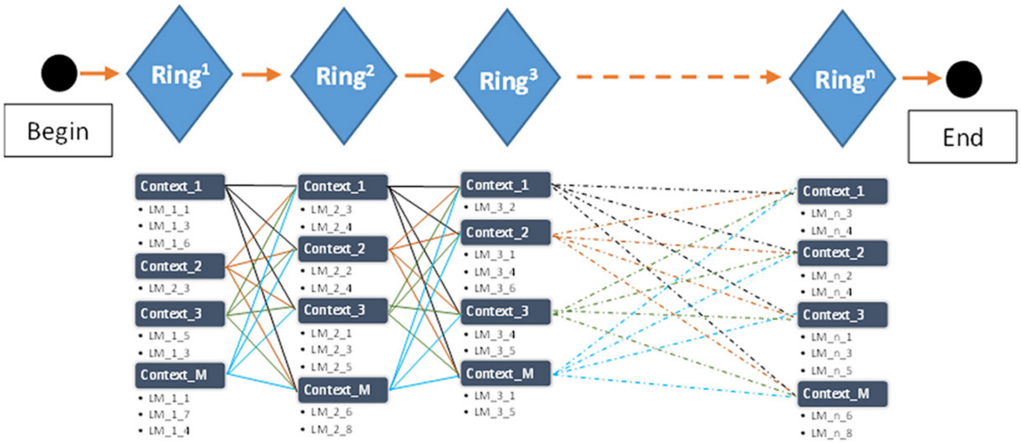

Fig. 6. All possible plans after executing the similarity algorithm

Sensors detection service: It automatically detects the real context of the learner. This service is responsible for identifying the available sensors in the learner's actual context. To accomplish this, the service employs a timer to detect the available sensors at regular intervals. By continuously updating the detected context dimensions (location, activity, and device), the service ensures that the learner's contextual learning style is accurately represented in the system. This allows the system to adapt to the learner's changing context and provide personalized learning experiences in real time.

Content adaptation service: It is built upon the preceding components described in earlier sections. It takes the detected context from the Sensors Detection service as input and represents it as a VARK vector, then selects the corresponding context from the M contexts of the learner. However, in the event that the detected context does not exist in the predefined contexts of the learner, the service applies cosine similarity between the detected context vector and the predefined contexts matrix to identify the most appropriate match. This approach avoids the need to repeat the process from the beginning and ensures that the appropriate learning materials are displayed. This process is repeated each time a new context is detected, enabling the system to continually adapt to the learner's evolving context and provide personalized learning experiences in real-time.

5 DISCUSSION

The approach we have proposed essentially supports learning adapted to learners' preferences. We have classified these preferences into four dimensions, which we consider the pillars of the contexts each learner can encounter. These dimensions are the learner's learning style, location, activity, and device. We have represented these dimensions by vectors of four characteristics each, which are those offered by the VARK model. Then, we made combinations to generate contexts represented by vectors with the same characteristics. The same work has been done with LMs and their effect on the corresponding rings for the actual courses using content-based similarity algorithms. (The cosine similarity algorithm is used in this work.)

By giving weights between 0 and 1 for each VARK feature, the learner will not be classified categorically as Visual, Aural, etc., as in [31], [9], [28] and others. In our approach, the learner's classification is partial: the learner is Visual with the percentage of W_v and Aural with the percentage of W_a, etc. Similarly, for any LM, the classification is also not categorical. Each LM presents a percentage of video, audio, textual, and kinesthetic content. This gives more flexibility, for both the courses' designers or learners, and richness regarding the content of the courses. For example, an LM with a high weight in the Visual feature will not be displayed for Aural learners in models of categorical classification. However, this LM could be selected for all learning styles in our approach.

We have adopted four dimensions to represent learning contexts, which are significant indices since they reflect the reality of the learning operation. This does not prevent anyone from being able to add other dimensions, since the representation of the context in the proposed approach is scalable.

The proposed approach provides the possibility of calculating the weights of the different dimension features in different ways, using functions, formulas, or machine and deep-learning techniques. Content adaptation is done during the planning process, using the cosine similarity algorithm in this approach. Other similarity algorithms could be tested to determine which gives better results. This axis will be addressed in our future work.

The assignment of LMs of each course ring to the corresponding contexts has made the adaptation of the context easier and faster. The system detects only the learner's current context and then makes the matching. Nothing is calculated from the beginning. (No weights are calculated for the detected contexts, and there is no need to make matching between contexts and LMs).

The number of possible plans generated for each learner differs from one learner to another, depending on the dimensions chosen. It equals the number of contexts generated, which is M to the power of the number of rings in the course, which is N. On the other hand, the adaptation of the content to the contexts is done only $M \times N$ times.

6 CONCLUSION

In this work, we have proposed an adaptive context-aware course-planning model. We focus on the contexts in which learners can find themselves during learning by offering them adapted courses' contents. We have considered that any learners' context is made up of four dimensions: the learners' learning style, the places or locations of the learners, the activities that the learners practice, and the learning devices. A learner can choose more than one item in every dimension. Next, we have presented each dimension by a vector of four characteristics of the VARK model with a weight for each. These weights are calculated differently based on each dimension's nature. We ended up generating or predicting several learning contexts for learners, where each generated context is also represented by a

VARK vector. The weights of the established context vector are the intersection of the dimension vectors' weights that compose it. In the same way, we have considered that a course is a chain of rings; each ring contains several LMs of the same content but in different formats. A VARK vector also represents any LM in the same way as contexts. Finally, we applied the similarity algorithm to select the LM that corresponds to each context. The possible plan that the learner should follow is a path between the possible contexts. Before starting learning, a learner can see all possible contexts and plans. As he begins to learn, an adaptation of the real context with one of the predicted ones takes place.

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