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ADAPTING LEARNING IN A CONTEXT-AWARE MOBILE LEARNING SYSTEM USING THE DYNAMIC CASE BASED REASONING

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ABSTRACT

Artificial intelligence has become an increasingly present technology in our daily lives and mobile applications are no exception. Artificial intelligence offers many advantages in the development of mobile applications, on the one hand improving the user experience and on the other hand opening up new possibilities for developers.

Learning is one of the areas concerned with the integration of artificial intelligence in the development of mobile applications, it is mobile learning which consists of using mobile devices to access content and educational resources at anytime and anywhere by adapting and creating individualized learning paths based on each learner's needs, interests and prior knowledge.

This article presents an approach to an adaptive learning system designed for mobile devices. This approach allows real-time personalized monitoring of the learner during the learning process, providing a personalized learning path based on observation of the context and centered on the learner using mobile devices. This monitoring is carried out using the Felder-Silverman learning style to detect the learning style of each learner, and the artificial intelligence approach of Case-Based Reasoning to ensure automatic prediction and adaptation to the dynamic changes in the behavior of the learner during the learning process (their profile and the characteristics of their mobile device) through the search for similar past learning paths.

Keywords: *Case-Based Reasoning, Mobile Devices, E-Learning, Artificial Intelligence, Adaptive Learning System, Context-Aware, Mobile Learning System, K-Nearest Neighbours*

1. INTRODUCTION

With the development of mobile technology and the widespread use of mobile devices, users are increasingly integrating these new communicating and intelligent devices into their learning processes. This is known as mobile learning.

Information and Communication Technologies in Education (ICTE) are evolving rapidly, incorporating new trends that are considerably changing the use of adaptive learning in education. One of these emerging trends is mobile learning, which enables learners to access educational resources on the move, using mobile devices. With the development of mobile technology and the widespread use of mobile devices, learners are increasingly integrating these new communicating and intelligent devices into their learning processes. This is known as mobile learning.

In general, mobile learning is increasingly emerging as an effective learning method, thanks to the use of intelligent mobile devices that are always operational and easily transportable, and that can be used anywhere, at any time and in any context [1].

The use of a mobile device in an adaptive learning system must allow for personalised monitoring according to the learner's context, which is based on certain factors such as the collection of various changes surrounding the learner (the profile and characteristics of their mobile device), the processing of these variables, real-time decision-making, etc. These points present the main challenges, particularly in terms of the compatibility of systems with the various devices and the connectivity and battery requirements, which can considerably reduce the effectiveness of learning in these systems. This requires a thorough review of pedagogical strategies by teachers, as well as an adaptation of course design methods to maximise learning effectiveness and minimise the abandonment.

These challenges can be limited through the integration of artificial intelligence (AI), which has become an increasingly prevalent technology in our daily lives.

AI offers many advantages in the field of mobile learning, making it possible to personalise and enhance the learner experience by offering relevant and tailored content. The benefits of AI in mobile learning include the ability to analyse learner behaviour, preferences and usage patterns to deliver personalised learning paths [2].

It also enables efficient management of device resources, such as battery consumption, connectivity and memory, making it possible to adapt learning resources to device resources.

In this paper, we present an architecture for an adaptive mobile learning system based on the artificial intelligence paradigm the Incremental Dynamic Case-Based Reasoning (IDCBR) [3], which supports and tracks the the learner in difficulty in real time through the different stages of the dynamic CBR cycle, recommending a relevant learning path through observation and comparison of his learning path with the learning paths of other learners with similar behaviors and similar mobile device characteristics.

The rest of this article is organized as follows: in the second section, we present mobile learning, context awareness in a mobile learning system and the approach to decision-making, the Dynamic Case-Based Reasoning. In the third section, we describe the proposed adaptive learning system approach and the various models making up the system and we finish by a conclusion

2. LITERATURE REVIEW

2.1 Mobile Learning

The emergence of new technologies has led to the emergence of new research and methodologies, as well as new projects. This covers most areas of science and engineering, and particularly mobile learning. Mobile technologies have brought new concepts and practices that are increasingly easy to integrate into different fields, such as mobile adaptation and context awareness. Lately, these concepts are being combined with the education domain to establish an important infrastructure to help teachers and learners use new approaches and technologies for teaching in mobile environments [4].

The field of mobile learning is very recent, addressing the relationship between teaching and learning using mobile technology. According to [5], this field can be defined:

- ✓ An extension of e-Learning [6]: since e-Learning enables content and services to be delivered electronically via a computer network linking learner and teacher. Mobile learning presents an intersection of e-Learning with mobile technologies ([7, 8, 9 and 10]);
- ✓ Learning carried out using mobile devices. Mobile learning is an extreme evolution of e-learning, in which the learner can follow a course using a mobile device [11];
- ✓ Learning based on the learner's mobility ([12 and 13]). In mobile learning, it is necessary to understand how learning activities are integrated with mobile technology [14].

In general, mobile learning is a type of e-learning that uses mobile technology to respond appropriately to the mobility of learners. This type of learning is defined as learning through a context that is centered on the learner using mobile devices.

2.2 Context awareness

According to [15], context is defined as "any information that can be used to characterize the situation of an entity. The entity is a person, a place, an object that is considered relevant to the interaction between the user and the application. In the context of mobile learning, it is necessary to take context sensitivity into account to adapt learning to different learners according to their needs and the characteristics of their devices. Context awareness is a delicate feature for a mobile learning system.

Indeed, it reflects the ability to react appropriately to modifications and changes in the context, due to the mobility of learners resulting in a change in location, connection, low or high bandwidth, in addition to the variability of mobile devices which can be characterized by a large or small screen and different operating systems, etc. So it's important that the mobile learning system reacts automatically and dynamically to these changes, and offers the learner context-appropriate learning resources

2.3 Case-Based Reasoning

Case-Based Reasoning (CBR) is a problem-solving approach that uses past experiences to solve new problems [2]. A very important feature of the CBR is its relationship with learning, it allows updating cases and learning new cases. Solving a problem using the Case Based Reasoning approach can be done through a typical cycle with a set of the following steps: Elaboration, Retrieve, Reuse, Revise and Retain [3 and 16]. A new cycle of Case-Based Reasoning (CBR) is proposed by [3], presented in figure 1, which makes it possible to deal with dynamic situations: this is Incremental Dynamic Case-Based Reasoning (IDCBR). The IDCBR cycle presents an adaptation of the classic CBR cycle with a change in the order of the steps (certain steps can be re-executed several times).

The IDCBR cycle contains two main steps [3]:

- ✓ **Initialization step:** this step makes it possible to develop the initial target case (Elaboration step in a classic cycle) from the description of the situation to be treated and to find similar source cases using a similarity measure (step of retrieve in the classical cycle). The goal of this step is to create a candidate list containing the source cases most similar to the target case;
- ✓ **Dynamic step:** detection of the first change in the target case causes the creation of a memory loop which leads to a new elaboration of the target case and an update of the list of similar source cases already created in the previous step. This loop is finished when there are no changes in the target case and it is activated each time the target case changes during the execution of the reuse step and the retrieve step (classic cycle) . If there is no change in the target case, the classic cycle is executed until the learning step.

The IDCBR is a continuous cycle which takes into consideration the dynamic and incremental change of the target case to be resolved, it makes it possible to stop the execution of certain steps and to re-execute others at each moment where there is a new change detected in the target case.

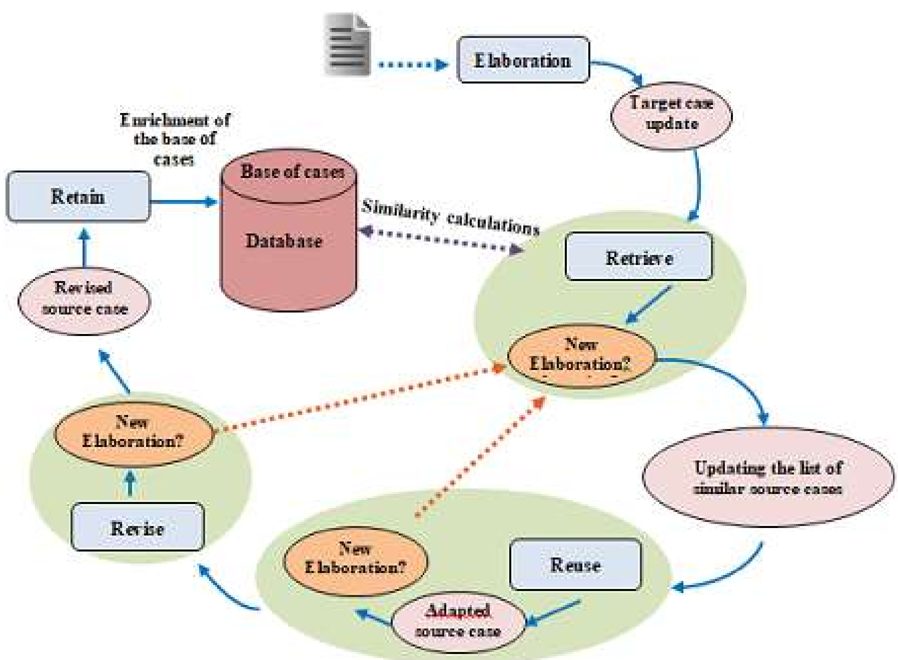

Figure 1: IDCBR cycle [3]

3. METHOD

Our proposed approach makes it possible to offer adapted and individualized learning to the learner in real time in a mobile learning system, using artificial intelligence techniques to automatically adapt to dynamic changes in the learning context during the learning process.

According to [17], context is divided into three categories:

- ✓ IT context;
- ✓ User context;
- ✓ Physical context.

According to [18] added a new context, it is the temporal context and according to [19]

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defined the context by four categories: identity, place, status and time.

In our mobile learning system, the context will be defined by three essential elements making it possible to represent all the information that characterizes a learning situation (figure 2):

- ✓ **Learner profile:** personal information, learning profile, prerequisites;
- ✓ **Educational objects:** learning objects, versions of learning objects which are presented according to type (course, exercise, algorithm, etc.) and format (text, audio, video);
- ✓ **Mobile device:** battery consumption, connection speed.

Our approach presented in Figure 3 allows us to:

- ✓ Detect the initial learner profile using the Felder-Silverman FSLSM learning style model [20 and 21], creating profile classes and providing an initial learning path for each learner.
- ✓ Monitor the learning of the learner in real time who has encountered learning problems using the Incremental Dynamic cycle of Case-Based Reasoning (IDCBR) [3], to offer them a path adapted to the dynamic change of their context.

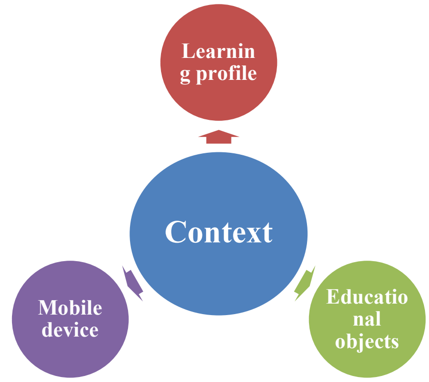

Figure 2: Elements constituting the context

Our approach is composed of four models:

- ✓ **Learner Model:** allows detecting the learner profile of learner;
- ✓ **Educational Model:** allows educational content to be presented in several formats and types;
- ✓ **Mobile Model:** allows you to collect and detect characteristics on mobile devices;
- ✓ **Adaptation Model:** allows you to adapt and individualize the content according to the learner model and the mobile model.

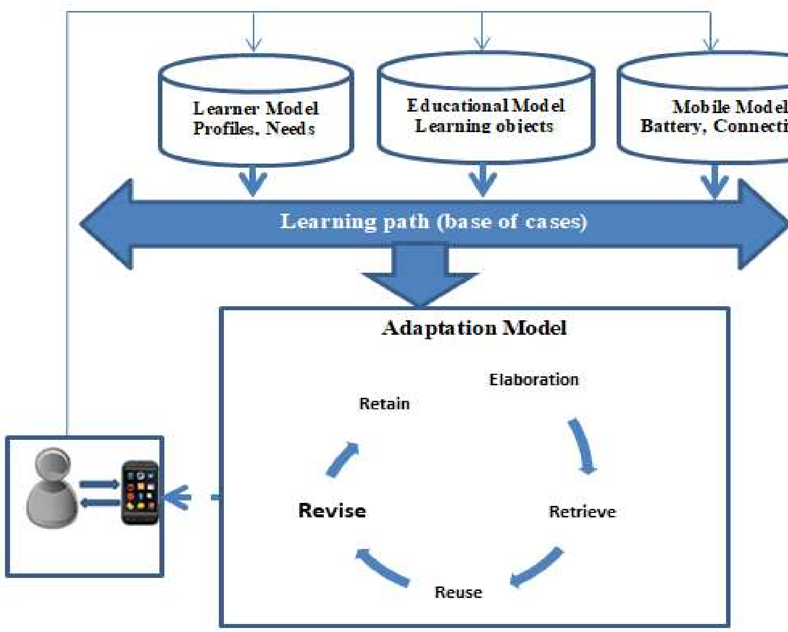

Figure 3: Proposed approach

3.1 Learner Model

Learner modeling is essential for generating individualized learning path. This involves describing the properties of the learner to which the system must adapt. These properties can be different from one learner to another and for the same learner, they can vary over time.

In our system, this model is essentially based on the FSLSM learning style model [20 and

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21] in order to know the learning preferences and needs of the learner.

The FSLSM learning style model classifies the learning styles according to 4 dimensions: Sensing/Intuitive, Active/Reflective, Visual/ Verbal and Sequential/Global. These dimensions respectively describe the variation of each learner's information perception, information processing, information reception and information understanding

The FSLSM learning style is obtained using the Index of Learning Styles (ILS) [22], which takes the form of a 44-question multiple-choice questionnaire used to assess the learner's preferences through their responses, quantifying each of the four dimensions using a score between -11 and +11.

This model is used to:

- ✓ Collect personal information from the learner such as username, password, last name, first name, age, email, country, etc. The acquisition of this information can only be done with an identification form that the learner must complete during their first contact with our system;
- ✓ Detect the learning style of each learner via the FSLSM learning style model. The choice of the FSLSM learning style model is due to the following reasons [23, 24 and 25];
- ✓ Propose an initial learning path, there is a relationship between educational resources and FSLSM learning styles as mentioned in the following table

Table 1: Recommendation of learning objects according to FSLSM [22, 23, 24 and 25]

FSLSM Learning Style		Recommendation of Learning Objects
Perception	Intuitive	Concepts and theories
	Sensing	Material facts and concrete data
Processing	Active	Linear text, chat, forum, emails, arrow based navigation
	Reflective	Case studies
Input	Visual	Graphs, tables, diagrams, images, video, demonstration, etc
	Verbal	Text-based material, including audio objects, hypertext, slideshows
Understanding	Sequential	Orientation, predefined learning paths
	Global	Open course structure, response system, etc

3.2 Educational Model

The educational model is based on a differentiated pedagogy [29] which allows for the diversification of content, in order to resolve the problems linked to the heterogeneity observed in the profiles of learners by diversifying the means and procedures of learning.

Differentiated pedagogy makes it possible to offer several versions of the same learning object and to check the relevance of each learning object for subsequent use (problems that may appear during learning).

In our case, we have divided the course into several units or learning objects numbered from 0 to n-1 (n represents the maximum number of learning objects in a course). Each learning object is represented in different formats (text, audio, and video) and types (definition, exercise, example ...)

3.3 Mobile Model

The FSLSM model describes the learning process according to four dimensions concerning the perception, processing, input and understanding of knowledge, each dimension of the FSLSM promotes learning.

The following table presents the correspondence between FSLSM learning styles and the characteristics of the mobile device.

Table 2: Correspondence between FSLSM learning styles and the characteristics of mobile devices

Recommendation of Learning Objects	Mobile device characteristics	
	Connectivity	Battery
Intuitive	High	Low
Sensing	Low	High
Active	Low	Low
Reflective	High	High
Visual	High	High
Verbal	High	High
Sequential	Low	High
Intuitive	High	Low

3.4 Model adaptation

After detecting the learner's learning style, which allows us to offer them a learning path based on their style. Each learner's learning process takes two scenarios:

- ✓ **Normal:** the system goes directly to the last step of the IDCBR which allows the learning style of each learner, their interaction traces and the characteristics of their mobile device to be recorded as a new case (a new experience successful) in the case base;
- ✓ **Abnormal:** when the system detects an anomaly or problem during the learning process. The IDCBR cycle is triggered to provide real-time monitoring.

In the second situation, the IDCBR adapts the learning process according to the profile and real behavior of each learner through: Observation of the learner's learning process (their learning path) and the characteristics of his mobile device.

In the adaptation model, the system must adapt learning based on the preferences, needs and mobile characteristics of each learner. It allows dynamic and individual supervision in real time via the IDCBR approach, which allows, through its different steps, to follow the learner at each moment of their learning in order to offer them learning adapted to their context.

4. DISCUSSION

Learning adaptation is a decisive element in the learning process. This adaptation is based on FSLSM learning styles and the characteristics of the mobile device, which poses a problem for dynamic change either at the level of the learner's behavior or at the level of the mobile device. This is why we used the IDCBR approach to manage dynamic situations and make decisions in real time, based on the learning needs of each learner and the mobile characteristics of their device in order to monitor them and to offer a path adapted to the dynamic change of the mobile learning environment. In the adaptation model, the dynamic CBR cycle is applied through the differents steps.

4.1. Elaboration

The role of this step is to detect the initial learning style of each learner through the results of the FSLSM questionnaire and to collect data so that the system can propose an initial learning path to begin the learning process. This step also collects the learner's behaviour by observing their traces in the system in real time and the characteristics of their mobile device, such as battery and connectivity. The data collected presents the learning path of each learner (target case).

The learning path for each learner is presented as follows:

Learning path$_{(ti,j)}$=learning traces$_{(ti,j)}$ + mobile device characteristics$_{(ti,j)}$

$$\textbf{Learningpath}_j=\sum_{i=0}^{i=n-1}\textbf{Learning path}_{(ti,j)}$$

Avec:

- ✓ j: presents the learner;
- ✓ t_i: presents the moment when the learner consults a learning object i;
- ✓ n: presents the maximum number of learning objects

4.2. Retrieve

This step detects learners with similar behaviour and the same mobile device characteristics (sources cases) as the learner in the learning situation (target case), by searching the database of source cases (learning path) using a similarity measure.

In this step, we will use the K-Nearest Neighbours method (KNN) [30 and 31]. The KNN is one of the methods of supervised machine learning [32] that is simple and easy to implement. It can be used to solve classification and regression problems.

It is necessary to classify the learners in difficulty in each learning moment in order to detect the class mainly represented by the K nearest learners. To classify the learners, by applying the KNN algorithm:

KNN algorithm (BC, k, TC t_i)

- **a.** Determine parameter k in general, the good value of K is √p, where p is the population (learning base) [33]. In our case, n presents the number of learners who have validated a course;
- **b.** For each i item (i from 0 to n-1)
- **c.** For each SC item in the BC
- **d.** Calculate and store the distance D between TC and the SC. ***/* Calculate the similarity between the Learning path(t_i,TC) and all Learning paths(t_i,SC) */***
- **e.** Store this distance and the associated data in a list of distance (D, SC).
- **f.** Sort the liste of distance in ascending order.
- **g.** Select the first K entries in this list.
- **h.** Obtain the labels of the k selected data from the BC.
- **i.** Retrieve the majority entrie.

Avec:

- ✓ n: presents the maximum number of learning objects;
- ✓ BC: presents the base of cases ;
- ✓ k :presents the number of nearest neighbours (learners) ;
- ✓ TC: presents the target case;
- ✓ SC: presents the source case;
- ✓ d: presents the Euclidean distance [34].

The result of this algorithm is to recover the majority entries (source cases) of the K-NN of the learner in difficulty from t_0 to t_{n-1}.

At each moment when the system detects a learning problem in the learning process, the K-NN algorithm will be applied through the execution of the retrieval loop [3and 35].

4.3. Reuse

The role of this step is to adapt the source case recovered in the previous step, by applying:

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✓ The solution proposed without change.
✓ The proposed solution with change.
✓ Human intervention.

4.4. Revise

This step allows the revision of the source case:

- If the chosen case presents the most similar source case.
- Otherwise, if the source case does not correspond to the target case. In this case, the system must return to the second step (Retrieve) to search for similar cases again.

4.5. Retain

When the learner completes his learning process and does not encounter any new learning problems, this learner (target case) becomes a new solved case and retained in the case base. This case is used immediately for solving future problems. The profile of this learner, the learning traces, the learning path and the characteristics of the mobile device will be saved in the case base as a new experience.

5. CONCLUSION

The proposed approach was designed for different learners with different characteristics in order to provide them with the appropriate learning that meets with their knowledge level and learning styles. Our contribution consists of proposing an approach allowing adaptive learning and individualized monitoring in real time in a mobile learning system. Our approach is based on the FSLSM learning style to detect the learner's initial style and the characteristics of their mobile device. Depending on the detection of the learner's context in the mobile system, a decision is made through the IDCBR approach is applied in order to create a personalized learning path adapted to the dynamic change in the behavior and characteristics of the mobile device of each learner.

Our future work consists in developing the different stages of the dynamic CBR cycle, by integrating other Machine Learning methods and multi-agent systems.

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