

AMBLE: A Context-Aware Mobile Learning Framework

Brita Curum^{1,*} and Kavi Kumar Khedo¹

¹University of Mauritius, Réduit

Abstract

INTRODUCTION: Mobile Learning is a new pivotal learning trend nowadays. With the increasing use of sophisticated smartphones equipped with augmented reality supporting tools and sensors, mobile learning platforms are expected to deliver tailor-made and customized learning elements to learners. Context-awareness is regarded as the fundamental approach or workaround to lift this learning style to distribute adaptive and personalized learning elements in mobile devices.

OBJECTIVES: The main priority in mobile learning is to make learning elements as flexible as possible using different forms of context data to extend the natural adaptation capabilities in mobile devices in order to engage learners in extremely rich environments.

METHODS: In this paper, A context-aware MoBile LEarning framework is proposed, namely the AMBLE framework. It processes contextual data at four distinct levels namely: Sensing Layer, Adaptation Layer, Context Processing Layer, and Application Layer to perform adaptation of learning contents based on the actual environment and conditions of the learner.

RESULTS: Partial implementation of the proposed framework has the potential to capture and represent the physical context information that may be used to perform a dynamic adaptation of learning contents and thus significantly improve the mobile learning experiences. Extra work is expected regarding the implementation of the other layers and components of the framework including the user model, context manager, and the adaptation engine.

CONCLUSION: The AMBLE framework proposes some relevant content adaptations with some positive results. As future works, new forms of user-context adaptation synthesized with other extracted data sets of contextual information will be used to establish and align relevant dynamic adaptation and personalization of learning contents.

Keywords: mobile learning, adaptive mobile learning, context-awareness, content adaptation, personalization.

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*Corresponding author. Email:brita_curum@hotmail.com

1. Introduction

Mobile learning is an engaging tool for innovative learning and its versatile characteristics will surely influence learning approaches in the next few years. Mobile devices nowadays are increasingly becoming sophisticated and are equipped with a wide range of sensors. With the enormous developments in mobile devices over the last few years, there is a greater demand for mobile learning without space and time barriers as supported by [1-2]. Moreover, it is now possible to develop effective context-aware mobile learning systems that dynamically adapt learning contents based on

the physical environment, device characteristics and learner profile. However, even with all the technological advancements, it is still challenging to capture the immediate surroundings of the learner and deliver adapted and personalized learning contents. Thus, these new capabilities of mobile devices need to be fully exploited to significantly improve mobile learning [3-5].

Using contextual information to support learning experiences through mobile technologies is an area which is lagging [5-7]. Also, the demand for contextualized, adaptive, situated and reliable educational materials that may be accessed through mobile learning systems is increasing exponentially [8, 9]. With the large scale impact

that mobile technologies bring in the educational sector and the new insights of mobile surveys that applications must engage in mobile-first characteristics [10-11], there is a need for content display across portable devices to be better formatted for viewing, reading, scaling and optimization [12]. Factors such as the actual location, device context, user-related context information which affect learning materials delivered on portable devices under varied circumstances have to be considered [13-14]. Partial attempts to adapt contents on mobile learning platforms have been made [15], with only reduced focus on context representations and content adaptation algorithms [16-17]. Research works in the field of context-awareness should be extended to combine different contexts' data categories for natural adaptation capabilities of learning contents in mobile devices. Moreover, there is a significant need to develop a potential contextual mobile learning framework that uses explicitly the learner's contextual information including the pedagogical conditions, cognitive loads, self-learning styles and many others to improve learning experiences in mobile learning. Indeed, content adaptation and personalization are important factors that could contribute to game-based educational materials to maximize the learner's learning motivation, effectiveness and satisfaction [18].

In this paper, A context-aware **MoBile LEarning** (AMBLE) framework is introduced that underpins a processed representation of contextual data at different levels to adapt the learning contents in synchronization with the actual environmental and learner settings. The proposed framework uses different levels of contextual information that may be used to perform dynamic adaptation of the mobile learning contents and thus significantly improve the learning experience of the learner. Section 2 describes and illustrates the AMBLE framework with its defined layers and architectural components. Section 3 presents the problem analysis and research hypothesis of the proposed AMBLE framework followed by Section 4 which covers the partial development phase and implementation process of the framework. Finally, Section 5 discusses the results and observations obtained from the learning experiments performed using the AMBLE framework and Section 6 concludes the paper.

2. A context-aware MoBile LEarning (AMBLE) framework

In this section, A context-aware **MoBile LEarning** (AMBLE) framework is proposed that performs dynamic content adaptation for personalized mobile learning. The different layers and architectural components of the AMBLE framework are defined and described. This framework has the potential to structure contextual data into composite forms to provide a smart, real-time and adaptive learning environment. Besides, self needs and requirements and behavioural aspects of the learner such as the learning comfort, ease of learning etc. are focused considerations to significantly improve learning experiences.

The AMBLE framework consists of four layers, each with distinct functions that are performing dynamic mobile learning content adaptation using contextual information. 1) **The Sensing Layer** uses different sensors to continuously monitor and capture raw contextual information of the learner's surrounding. This layer consists of two components which are the *Sensor Data Acquisition* that captures the most relevant information from different sensing resources and the *Sensor Classification* that perform an initial classification of the captured information. 2) **The Context Processing Layer** is the core layer of the AMBLE framework with five major components as follows: I) **The Context Acquisition**: Collected sensor information from the sensor layer are transferred to this component where appropriate functions are used to filter the context data about the learner's information, the mobile device and the current learning environment. II) **The Context Manager** receives context data from the Context Processing Layer and processes the data into distinct contextual categories (Intrinsic and Extrinsic Context) to perform appropriate representation of the different contexts. III) **The Physical Model** uses different physical contexts to derive an understanding of the current environment of the learner. For example, physical context parameters such as low bandwidth, high display resolution and high noise level are aggregated to determine the current environmental condition of the learner. IV) **The User Model** processes all the behavioural, pedagogical, and cognitive characteristics of the learner for appropriate personalization of the learning contents. V) **The Adaptation Engine** implements all the logic for carrying the adaptation of the learning contents based on the Physical Model and the User Model. The adaptation logic based on probabilistic or deterministic functioning of interpreted contextual information is processed by the adaptation engine. 3) **The Application Layer** in the AMBLE framework provides the necessary interface to application developers to deliver adapted learning contents from the Adaptation Engine to learners. Figure 1 below illustrates the different compositions of the AMBLE framework.

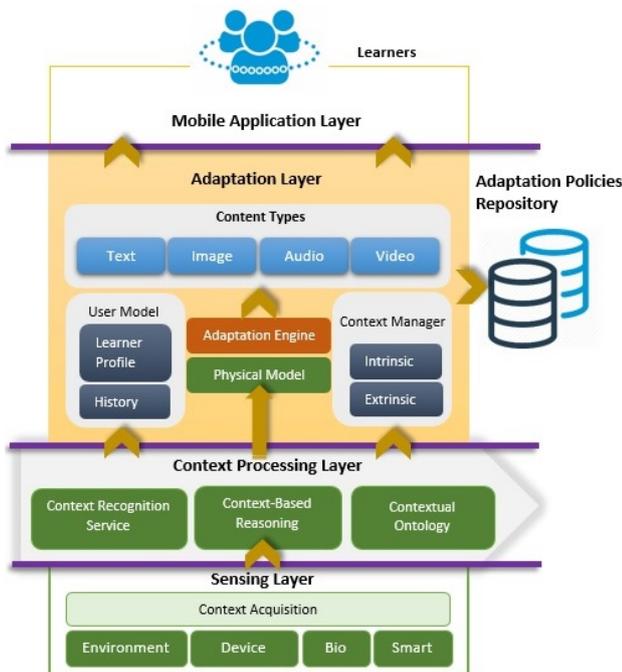


Figure 1. The AMBLE framework.

3. Problem Analysis and Research Hypothesis

In this section, the research challenges for the development of the AMBLE framework are identified and discussed. The research hypothesis for the framework is also defined.

3.1. Problem Analysis Overview for the development of the AMBLE framework

(i) Physical Characteristics of mobile devices.

There are several technical challenges related to mobile devices that need to be addressed for the realization of a fully context-aware adaptive mobile learning system. These challenges include incompatible mobile devices capabilities such as varying OS or non-standard mark-up language extensions, storage capacity, supported media formats and so on. Often the delivery of learning materials is inconsistent with the intended mobile devices [19]. Also, the physical features including the energy level such as the battery life of mobile devices, the small screen sizes and the limited processor’s capacities are regarded as main drawbacks in the development of context-aware mobile learning systems. In a media-rich context-aware mobile learning platform, it is obvious that the battery consumption level will increase drastically. Therefore, solutions must be found to resolve this issue. Methods of optimizing the deployed content types based on the device capabilities, bandwidth capacity, and supporting OS should be investigated.

(ii) Contextual data in mobile learning platforms.

Existing mobile learning platforms capture and use only basic context data such as time and location. More complex contextual information should be used for accurate learning materials delivery and adaptive mobile learning [20]. Shifting the interest to other contextual data such as infrastructure (network connectivity), user-centred data (preferences, pedagogical approaches, behaviours, etc.) is equally important to achieve a full-fledge context-aware mobile learning system. Moreover, with the latest mobile technologies including several innovative sensors, the capture of new contextual information of the learner is now possible. These captured contextual data can be used to provide a personalized and adaptive mobile learning system. Only a few mobile learning systems considered using the learner’s individual needs and requirements, their cognitive levels and pedagogical characteristics to deliver the best-suited and adapted learning content. Therefore, to overcome the described shortcomings, content adaptation based on contextual information and personal attributes of the learner is important for better mobile learning experiences. However further works are required in the areas of context acquisition, context representation and context-based reasoning for the realisation of such a learning system.

(iii) The learner’s instructional approach.

Another challenge for the provision of the AMBLE framework is the integration of contextual information with the individual pedagogical preferences and learning style of learners. At the moment, mobile learning systems do not adapt to the individual pedagogical preferences of learners based on their current situations or environment. Most mobile learning systems provide a common one-size-fits-all learning interface to the learners which are often difficult to customize the learning activities as per their individual needs and preferences. The ability to customize the different options to manage the learning materials for the requirements of individual learner is missing. For instance, an individual may prefer learning textual contents to be displayed while navigating through the media elements such as images, whereas another learner could opt for the display to be in a popup format.

(iv) Need to adapt to the cognitive level of the learner.

When no adaptation occurs, the learners are often presented with learning materials that may not be appropriate to their learning style. Therefore, the learner has to put in extra efforts to understand the learning contents and this raises the cognitive burden on the learner. Moreover, as seen from the evaluated cognitive frameworks, there is practically no use of relevant context-aware parameters to manage cognitive issues in mobile learning. The ability for learners to create their own learning spaces based on their prior experiences, preferences and needs together with the cognitive load management will allow the development of a personalized learning environment. Indeed, the development of

adaptation strategies that adapt the mobile learning contents based on the cognitive level of the learners is still an unexplored research area.

(v) Need to explore new adaptation strategies.

Adaptation strategies in mobile learning have been limited to static adaptation techniques and more dynamic adaptation are required that consider the user-centred context. Existing mobile learning systems use basic context data such as location and time and limited integration of internal context (user context) to perform a dynamic adaptation of learning contents is observed. More advanced adaptation strategies are required to optimize the mobile learning contents based on the hardware and software capabilities of the mobile device, the user conditions and the environmental contexts.

A radial Venn diagram is used to summarize the problems identified for a new personalized and adaptive mobile learning framework. The five nodes define the issues that need particular attention for the development of the AMBLE framework and form the underpinning of the proposed research in this paper.

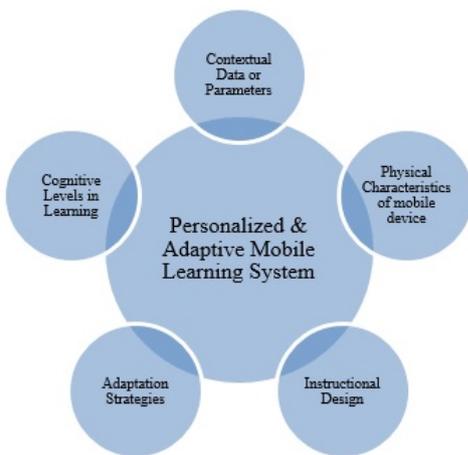


Figure 2. Problem-centred Radial Venn diagram.

3.2. Formulation of the Research Hypothesis

The challenges that need to be addressed are 1) the need for a context-aware framework for mobile learning. Developing the AMBLE framework involves a series of steps for effective and efficient contextual learning contents to be delivered to the learner. 2) With the wide range of sensors that exists in smartphones, the need to explore new adaptive techniques will allow students to be more receptive as it will allow flexible access to the contents anytime and anywhere. 3) Consequently, the need for dynamic content adaptation in mobile learning platforms is essential. The contextual system must allow students to learn under different contexts or situation. Fluctuations in their current location and environmental elements such as noise, light etc. must not limit their learning process. 4) Finally, the need for a

personalized mobile learning framework remains a challenge. Students should be provided with choices to adapt the learning contents based on their past skills or knowledge, prior experiences and behaviours etc. to develop their learning patterns.

Based on the extensive literature review and problem analysis carried out, the following research hypothesis is concluded for the AMBLE framework:

“A novel context-aware personalized mobile learning framework using dynamic adaptation strategies can significantly improve content adaptation in mobile learning platforms.”

4. Implementation of the AMBLE framework

This section discusses the partial implementation of the proposed AMBLE framework based on the outlined research hypothesis. In the prototype implementation, only the Physical Model and the Sensing layer have been considered. The development of the other components and the evaluation of the overall AMBLE framework are planned as future works.

4.1. Partial AMBLE framework development

From the overall AMBLE framework described in Section 2, only the components highlighted in green as shown in Figure 1 have been partially implemented. It involves mainly the Sensing Layer, the Context Processing Layer and the Physical Model from the Adaptation Layer. The implementation details are illustrated in the following subsections.

4.2. The Physical Model

Figure 3 below defines the Physical Model of the AMBLE framework. It consists of three sub-layers of adaptation. Each sub-layer is described in this section. Some initial parameters have been defined in the Physical Model and these will be further refined during the implementation process of multiple sections of the framework as more understanding on the learning context is derived.

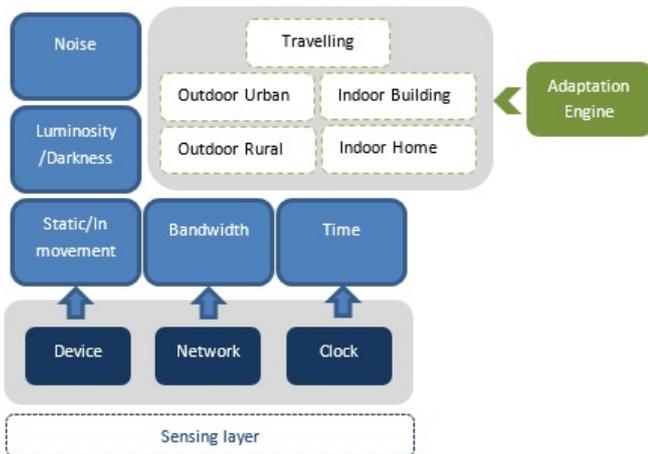


Figure 3. The Physical Model of the AMBLE framework.

The First level of adaptation

The device, network capabilities (bandwidth) and clock (time) are the three physical contexts that the AMBLE Framework uses as the first level of adaptation to progress with the generation of dynamic and personalized learning contents. The following segment describes the three physical contextual factors considered for performing content adaptation in the proposed framework.

- **The device**

The device stands as the core tool which acts as an interface between the Sensing Layer and the mobile operating system to retrieve important contextual information. Most of the sensors available in common devices have been exploited to define as accurately as possible instant context interactions between the learner and the device.

- **Network Capabilities (Bandwidth)**

The rapid alteration of the bandwidth over time and space is a piece of important contextual information to consider while delivering learning contents. For example, with a low bandwidth, streaming of high definition (HD) videos would lag. Instead, lower stream quality can be considered as an option for a smooth and continuous learning experience. As the bandwidth increases, a myriad of content types can be auto-selected to merge the existing array of content types forming a new selection of learning elements based on the different contexts information available.

- **Clock (Time)**

Time at which learning is taking place is also considered at the first level of adaptation. Depending on the preferences of the learner, time context may be used to generate learning contents with varying complexity in the selected lessons which help in maximizing the user’s knowledge level.

The Second level of adaptation

The second level of adaptation reacts mainly to movements of the learner, the light intensity and the noise level in the environment. Motions such as the acceleration, rotation and orientation are captured. Moreover, the luminosity in the surrounding during learning sessions is captured. Reading under too high or too low light intensity can disrupt the normal learning pattern and negatively impact the learning experience. Therefore, it is important to recalibrate the luminosity level of the device based on the lighting condition of the immediate environment. The noise level is another contextual information that this layer considers to adapt the audible state during learning.

The Third level of adaptation

Adaptation in the third level is based on the type of learning environment and is categorized into five main types. These are Travelling, Outdoor Urban, Outdoor Rural, Indoor Building and Indoor Home. This environmental context mainly works through the geographical position of the learner. From Figure 3 above the Outdoor Urban environment refers to mostly crowded and noisy settings; examples can be a university cafeteria or a shopping mall which is a crowded and noisy environment most of the time. Outdoor Rural surroundings refer to places which are less crowded and relatively less noisy. The Indoor Building considers classrooms settings referring to a fairly quiet environment while Indoor Home defines a reduced amount of noise intensity and cosy places, for example, the learner’s living room.

4.3. The Adaptation Engine

The adaptation engine is the core component in the AMBLE framework. It uses information from other components to perform the best suited adaptation of the learning materials. The Adaptation Engine is responsible for the delivery of personalized and adapted learning contents based on the presented context information from the learner, the environment and the device. Currently, sources from the Physical Model such as the activity of the learner, the location of the learner, noise level and the light intensity are used to perform adaptation. The adaptation engine processes context information using a predefined set of algorithms to accurately determine the situation of the learner. The results obtained are organized in an array of probabilities that falls within distinct threshold values. These information are then used to adapt and personalize the learning contents as per the different adaptation policies.

4.4. The implementation process of the AMBLE framework.

This section provides the details of the partial implementation of the AMBLE prototype. A brief

explanation of the context acquisition methods used by the Physical Model is provided.

Context Acquisition method used in AMBLE

This section briefly describes the context acquisition method used in the AMBLE prototype. Three components are defined to form an initial operational version of the AMBLE framework which will be implemented. The three components are the instructional contents, the software (AMBLE framework) and the database.

- **The Instructional Contents**

Proper instructional design rules are used to validate the learning contents that may be accessed across any ranges of mobile devices (tablets or phones). Consequently, the AMBLE framework is made compatible with different browsers such as Safari, Google Chrome, Firefox, all versions of Internet Explorer (IE) and is mobile-compliant.

- **The Software (AMBLE framework)**

The following techniques and algorithms are used for the development of the AMBLE framework:

- (i) *A Fused Location API* is used to retrieve and update the actual location of the learner. It determines whether the learner is at home or not. The location information remains constantly updated as movements are detected.
- (ii) *An Activity Recognition API* defines the actual activity that the learner performs and is updated as soon as an activity or action is detected. A Google API Client is used to allow for any activity update through the integrated sensors in the device. Predefined patterns in the API Client allow for automatic detection of activities such as travelling, running, walking and others.
- (iii) Measured in decibel, the *noise meter algorithm* compensates for the noise level in the surrounding environment and adjust the volume of learning contents where required. A recorder is initiated which sets the audio source of the content and retrieves the value in terms of amplitude, defines its format and encodes the content for proper output in the interface.
- (iv) *A light meter algorithm* processes the light intensity defined in the framework. The same principle as the noise meter is used where the light intensity values generated from sensors are checked against a set threshold value and the brightness of the device is adjusted accordingly.

- **The Context Adaptation Engine Algorithm**

The adaptation engine uses a customized algorithm to perform content adaptation based on contextual information for personalized and adaptive learning. This algorithm generally uses the most reliable sequences of context information from a broad array of probabilities to determine changes in the framework. The mechanisms

originated for the AMBLE framework keeps track of all the instant changes that occur in the context data values and compute the distinct possibilities. For instance, to determine the right environment that the learner is currently in, the algorithm considers the sum of all the probabilities that falls in one of the Context Recognition Layer's thresholds set. Once the situation of the learner is determined, the adaptation engine uses a set of adaptation policies to generate personalized and adaptive learning contents.

- **The Learning Media Optimizer Algorithm**

The Learning Media Optimizer adjusts the media elements (pictures, video, audio) being delivered based on the current internet connection speed to allow a smooth information flow and a better learning experience. Media components in the AMBLE framework are streamed based on the current connection speed and as a result, learning contents that contain HD video, animation, and high-quality images are adjusted accordingly.

- **The Database**

To allow accurate information flow within the AMBLE framework prototype while executing the above-defined functionalities, a database is implemented to store all the context data during the process. The context data tables in the AMBLE framework are given in 3NF for data redundancy reduction and improved integrity of the connected context data. Different tables were created based on the context data captured for different nodes. Moreover, the Adaptation Policies database contains information about the different types of adaptation and related logic.

5. Results and Discussions

This section reports on the initial evaluation carried out on the partial implementation of the AMBLE framework. Two types of test cases (Atomic and Compound) have been derived for the Sensing layer, the Context Processing Layer and the Physical Model components of the framework. The Atomic test case includes only one single unit of context data captured to determine the level of adaptation on a stand-alone basis. On the other hand, the compound test case covers a wide range of possibilities of a mixture of contextual data retrieved that validates further the assessment process. Experimental scenarios were set up to exercise the different situations of the learner and to assess the actual state of the different components in the framework. The initial results obtained are reported below.

5.1. Preliminary Results

A series of tests were carried out on the Sensing layer, the Context Processing Layer and the Physical Model in the AMBLE framework. The preliminary results for the different tests carried out are described in this section.

- (i) *The Fused-location API and Geofencing:* the captured Geolocation data in the application was tested using the Lockito android application. This tool allowed the setting up of fake environmental geo-positions which allowed the follow-up and full control over the speed and GPS signal accuracy. In this way, many static locations were defined and tested across the AMBLE framework. A pivot system was also employed to calculate the virtual geographic boundary between two regional coordinates. This distance was calculated and recorded.
- (ii) *Noise meter:* A professional noise meter was used to test the accuracy against the level of noise captured in the framework. With the measurements obtained, distinct and matching arrays of noise conditions were captured and analysed. Measurements were taken in decibels. An average percentage error is noted from an accuracy test which is 7.2% and is considered acceptable for portable devices.
- (iii) *Activity Recognition API:* Based on individual learner's activities, the AMBLE framework was able to track actions through the Activity Recognition API. Multiple test cases have been set to assess the distinct activities completed by the user. The occurring activities were saved in order of their matching probabilities. The table below illustrates five different activities ranging from in movement to static positions of an individual. The threshold value set for each activity is 75%. Activity recognition is seen to match the actual current activity that the learner performs. For instance, for travelling the activity recognition reflects a percentage value of 97% which is much higher than the threshold value set.

		around	Running: 2%
4	Static	Scale representation of being idle / Static – while holding the mobile device in a steady position	Travelling: 0% Static: 98% Unknown: 2%
5	Unknown	Scale representation for some random movements	Travelling: 15% Static: 0% Unknown: 85%

- (iv) *Light intensity:* The light intensity captured by the AMBLE framework through different devices was cross-checked against a professional light meter. The light intensity values from the AMBLE framework showed an average percentage error of 6.5% when compared with the professional light meter. The white box testing method has been opted for light intensity. An onSensorChanged() function was used to retrieve the sensor reading at short intervals update.
- (v) *The Physical Model Adaptation Testing:* Two groups of tests were defined to perform the Physical Model adaptation testing. The first group concerns atomic parameters, where adaptations are based on single context information and the second group concerns compound context parameters where adaptations are based on a combination of context parameters.

• **Atomic context parameters testing**

Table 2 below shows the different tests carried out based on the atomic context parameters detected and the corresponding adaptation that was performed by the AMBLE framework.

Table 1. Test cases for different activity performed by the learner

Test case	Different activity performed by the learner		
	Activity	Description	Activity Recognition
1	In movement: Travelling	Scale representation of movement - travelling by car or bus which was beta-tested in the framework	Travelling: 97% Walking: 1% Static: 2%
2	In movement: Running	Scale representation of movement – Under jogging / running conditions	Travelling: 0% Walking: 5% Running: 95%
3	In movement: Walking	Scale representation of movement – while walking	Travelling: 2% Walking: 96%

Table 2. Atomic parameters tested – Physical Context

Physical Context Monitored	Atomic Parameters		
	Interpretation of Parameter	Parameter Classification	Adaptation Outcome
Travelling	The getConfidence function and Activity Recognition API are used to detect the learner's movements or activities	Captures movement and uses the google geolocation API to detect the current location of the learner	Retrieves and responds correctly to the right and current environment of the learner
Static or In	The	Captures	The

Movement	getConfidence function is used to detect in motion physical context value	the movement and activities of the learner. Examples are rotation, tilting, acceleration and others	movement and activities of the learner are monitored under this physical context		intensity in the current setting		the learner (either idle or in movement) Contents are dependent on the varying intensities of noise and light, the bandwidth that the device captures and the current activity of the learner (either idle or in movement)
Luminosity / Darkness	High fluctuations of light intensity based on the current environment of the learner	Light intensity	Adaptation of lighting conditions respond correctly to the thread set to evaluate the light intensity	Outdoor rural	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and detects the noise level and light intensity in the current setting	Noise level, light intensity, activity, bandwidth	Contents are dependent on the varying intensities of noise and light, the bandwidth that the device captures and the current activity of the learner (either idle or in movement)
Noise	The noise level fluctuates based on the surrounding conditions	Noise level	Detects the noise level in the actual environment. Moreover, the learner is notified of a connected earpiece in the device while learning occurs	Indoor building	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and detects the noise level and light intensity in the current setting	Noise level, light intensity, bandwidth, activity	The application captures the current location of the learner based on the Google Map API with the connecting bandwidth ID, being saved as "home"
Network (Bandwidth)	The network bandwidth fluctuates as per the network conditions	Nearby network capabilities	Learning Elements are adjusted based on the fluctuations values obtained				
Time	Retrieves the actual time of the day or night	Four categories of time have been defined which are morning, day, afternoon and night	Adaptation of contents are matched to the four categories after processing of raw contexts have been executed				
Outdoor urban	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and detects the noise level and light	Noise level, light intensity, network conditions, any happening activity during the learning process	Contents are dependent on the varying intensities of noise and light, the bandwidth that the device captures and the current activity of				

• **Compound context parameters testing**

A combination of context information was monitored and tested at different time interval when learning takes place. Table 3 below lists the different scenarios that were captured by monitoring and combining several context parameters.

Table 3. Compound parameters tested – Physical Context

Physical Context Monitored	Compound Parameters	
	Interpretation of parameter	Adaptation outcome
Travelling + Device (Static or in movement or Darkness / Luminosity or Noise) + Network + Time	The travelling context in combination with other physical contextual parameters	Adaptation is directly proportional to the fluctuations of the processed results from the raw context values. Learning contents adapt

		well based on the combined contextual conditions			enhanced
Outdoor Urban +Device (Static or in movement or Darkness / Luminosity or Noise) + Network + Time	The outdoor urban context result was used in combination with other raw contextual values	The contents get adapted with the most subtle content types such as more images to merge the situation in the outdoor urban area	Indoor Home +Device (Static or in movement or Darkness / Luminosity or Noise) + Network + Time	The Indoor Home context in combination with other physical contextual parameters of the indoor environment	Indoor home is characterized as a quiet and best environment for learning provided that the noise level is low and that other conditions to support learning are met. Therefore, adaptation for noise is not so strict. Contents on the mobile device are adjusted based on the dim or high light intensity inside the house
Outdoor Rural +Device (Static or In movement or Darkness / Luminosity or Noise) + Network + Time	Starting with the Outdoor rural context, other physical contextual parameters were monitored in combination	The Outdoor rural environment defines a rather peaceful (fewer crowds, therefore, limited noise) surrounding for learning to take place. In this setting, the educational contents get adapted with more detailed learning elements (texts) rather while taking into consideration other context nodes such as light intensity, noise level and the other defined context			
Indoor Building +Device (Static or in movement or Darkness / Luminosity or Noise) + Network + Time	The indoor building context in combination with other physical contextual parameters	The learning contents are adapted with possibilities of mixed content types in the serene setting while taking care of the other different contextual parameters. Thus, the learning process is			

The above table illustrates the different real-life conditions detected by the AMBLE framework based on the current location of the learner. The framework has responded accurately to the distinct recognized physical environments for the delivery of adapted learning contents. However, when there are rapid fluctuations in environmental conditions such as in light intensity, noise level and network conditions, some delay to readjust the learning contents were noted.

5.2. Discussions

In this section, the achievements of the partial implementation of the AMBLE framework are discussed and the areas for further improvements are identified.

The partial implementation of the AMBLE framework has considered only the Sensing Layer, the Context Processing Layer and the Physical Model. Therefore, only a set of physical contexts has been captured, interpreted and used to perform an initial adaptation of learning contents. Extra work is expected regarding the implementation of the other layers and components of the framework including the user model, context manager and the adaptation engine. Most of the physical characteristics of the mobile devices being captured by the AMBLE framework can significantly be processed to deliver adapted learning contents to different screen sizes and varying operating systems.

Initial testing results of the AMBLE framework indicate accurate detection of the immediate physical environment

and a good flow of adapted contents based on all the physical contextual data received. Factors such as the current time, location of the learner, the activities performed together with the background noise and light levels captured are dynamically adapted and thus improves learning conditions. So far only the physical contextual data have been used in the framework. Only the technical feasibility of capturing the different physical contexts and performing some corresponding adaptations are determined. Context information such as pedagogical and behavioural (User Model) are yet to be explored for personalized and adapted mobile learning. Some test cases were set up to monitor the performance of an array of distinct categories of context information recorded during a learning session. These scenarios were classified into the atomic and composite context parameters test cases.

The construction of personalized learning options for learners is the next step of development in the AMBLE framework. The pedagogical preferences of the learner are important factors to consider. These will be considered by the User Model (the learner's details, thinking process, learning styles, preferences, etc.) as defined in the framework. Further adaptation will be performed based on the learners' interactions with services provided to them through the framework.

The cognitive node in the user model should provide further options to better capture the learning aptitudes of the learners. The knowledge level of a learner will be determined by using a combination of the time spent on lessons and assessments or short quizzes. The results obtained will be used to further refine learning contents based on the performance of an individual. From the Cognitive load Theory (CLT) principles, the extraneous load would be reduced to the maximum and the intrinsic and germane loads in learning would be regulated accordingly. The focus will be on the germane loads which will inevitably help the learners to maximize their concentrations on specific learning contents and as a result improves the learning patterns.

The adaptations performed by the prototype implementation of AMBLE are currently based on contextual physical data captured from sensors in the device. This is the initial step in the construction of the AMBLE framework. More contextual data contributions need to be addressed to provide an even better adaptive context-based mobile learning tool.

Up to now only features such as activity recognition and location detection accuracy have been developed and tested. A thorough evaluation needs to be established to perform a large scale acceptance test at different levels (pedagogical, learners, device and system capabilities) to determine to what extent the AMBLE framework is improving the learning experiences of the learners. This investigation would bring to light the strengths and weaknesses of the AMBLE framework for mobile learning.

6. Conclusion

The proposed AMBLE framework which consists of four layers namely: Sensing Layer, Adaptation Layer, Context Processing Layer, and Application Layer underpins a processed representation of contextual data at different levels to adapt learning contents in synchronization with the actual environmental and the user settings. AMBLE has the potential to capture and represent the learner's context information that is used to perform dynamic adaptation of learning contents and thus significantly improving the learning experience of the learner via a mobile device.

The partial implementation of the AMBLE framework can capture five environmental conditions including travelling (learner moving); outdoor urban environment (crowded and noisy settings); outdoor rural surroundings (quiet outdoor settings); indoor building (inside a building such as school); and indoor home (cosy places such as the learner's home). This set of contextual parameters is considered to carefully analyse their impacts and determine appropriate content adaptation being performed for a better learning experience. Indeed, the initial results of the partial content adaptation based on the physical contexts showed the potential for improving the mobile learning experience of the learners.

As future works, the development of the other components of the AMBLE framework needs to be carried out and a thorough evaluation needs to be performed. The additional contributions to the AMBLE framework include 1) Context Acquisition and Context Representation: A high-level context recognition pattern including context reasoning, modelling and ontology to allow appropriate logical interpretations of the context data. Formulation of the User Model: identifying the aim, objectives and intentions of a learner is still a challenge for the delivery of adaptive and personalized learning contents. The cognitive theories should be incorporated in the framework which will ultimately intend to reduce the ambiguity in the representations of learning resources, enhance understanding, and critical thinking. Moreover, a pedagogical component needs to be developed, that assesses the psychological and behavioural aspects of the individual learner and allows the provision of distinct learning styles adapted to the learner. 2) The development of the Application Layer to allow relevant interactions with services provided by the AMBLE framework. This layer will act as an interface for the implicit and explicit exchange of data from and to the mobile learning application. 3) On top of all these functionalities which needs to be implemented, the introduction of a cloud-based storage system cannot be ignored. With the flow of information at different nodes from the AMBLE prototype, it is inevitably true that a robust storage service will provide possible solutions to managing the dynamic spread of context data and offloading of adapted learning contents [21]. Finally, an in-depth evaluation needs to be performed for the instructional representation of contents while combining both the user and physical models. Metrics for evaluating the performance of the dynamic content adaptation and personalization will be derived. Moreover, some acceptance

tests need to be performed to carefully analyse and measure the effectiveness of the framework for the provision of a

dynamic context-aware personalized and adaptive mobile learning system.

References

- [1] LAM, J., YAU, J. AND CHEUG, S., 2010. A review of mobile learning in the mobile age. In: *Proc. 3rd International Conference on Hybrid Learning, Lecture Notes in Computer Science Springer*, Berlin, 6248, pp. 306–315.
- [2] OSSIANILSSON, E., 2018. Promoting Active and Meaningful Learning for Digital Learners. In *Handbook of Research on Mobile Technology, Constructivism, and Meaningful Learning*, pp. 294-315. IGI Global.
- [3] FOTI, M.K. AND MENDEZ, J., 2014. Mobile learning: How students use mobile devices to support learning. *Journal of Literacy and Technology*, 15(3), pp.58-78.
- [4] MANAKIL, J. AND GEORGE, R., 2017. Mobile learning practices and preferences a way forward in enhancing dental education learning experience. *European Journal of General Dentistry*, 6(1), pp.22.
- [5] Ahmed, S., Javaid, S., Niazi, M.F., Alam, A., Ahmad, A., Baig, M.A., Khan, H.K. and Ahmed, T., 2019. A qualitative analysis of context-aware ubiquitous learning environments using Bluetooth beacons. *Technology, Pedagogy and Education*, 28(1), pp.53-71.
- [6] ROZARIO, R., ORTLIEB, E. AND RENNIE, J., 2016. Interactivity and mobile technologies: An activity theory perspective. In *Mobile learning design*, Springer, Singapore, pp. 63-82
- [7] Chung, C.J., Hwang, G.J. and Lai, C.L., 2019. A review of experimental mobile learning research in 2010–2016 based on the activity theory framework. *Computers & Education*, 129, pp.1-13.
- [8] COOK, J., 2010. Mobile phones as mediating tools within augmented contexts for development. *International Journal of Mobile and Blended Learning (IJMBL)*, 2(3), pp.1-12.
- [9] Çakmak, F., 2019. Mobile Learning and Mobile Assisted. *Language*, 1(1), pp.30-47.
- [10] Mumba, P. and Lengwe, M., 2019. Examining Factors Influencing the Adoption mobile application in collaborative learning. *Zambia ICT Journal*, 3(1), pp.5-13.
- [11] Narayan, V., Herrington, J. and Cochrane, T., 2019. Design principles for heutagogical learning: Implementing student-determined learning with mobile and social media tools. *Australasian Journal of Educational Technology*.
- [12] MASIE, E., 2013. The Future of Mobile Learning [Online].
- [13] SHIH, J.-L., CHUANG, C.-W. AND HWANG, G.-J., 2010. An Inquiry-based Mobile Learning Approach to Enhancing Social Science Learning Effectiveness. *Educational Technology & Society*, 13 (4), pp. 50–62.
- [14] JALDEMARK, J., 2018. Contexts of Learning and Challenges of Mobility: Designing for a Blur Between Formal and Informal Learning. In: Yu S., Ally M., Tsinakos A. (eds) *Mobile and Ubiquitous Learning. Perspectives on Rethinking and Reforming Education*. Springer, Singapore.
- [15] ZERVAS, P., DEMETRIOS G. AND SAMPSON, 2013. Context-aware adaptive and personalized mobile learning systems. *Ubiquitous and mobile learning in the digital age*. Springer New York, pp.3-17.
- [16] EL-HUSSEIN, M.O.M. AND CRONJE, J.C., 2010. Defining mobile learning in the higher education landscape. *Journal of Educational Technology & Society*, 13(3), pp.12.
- [17] ZAFAR, A. AND HASAN H., S., 2014. Towards Contextual Mobile Learning. *International Journal of Modern Education and Computer Science (IJMECS)*, 6(12), pp.20-25.
- [18] ALSUBAIE, A, ALAITHAN, M, BOUBAID, M. AND ZAMAN, N., "Making learning fun: Educational concepts & logics through game," 2018 20th International Conference on Advanced Communication Technology (ICACT), Chuncheon-si Gangwon-do, Korea (South), 2018, pp. 454-459.
- [19] YOUSAFZAI, A., CHANG, V., GANI, A. AND NOOR, R.M., 2016. Multimedia augmented m-learning: issues, trends and open challenges. *International Journal of Information Management*, 36(5), pp.784-792.
- [20] CHEN, C. H., LIU, G. Z. AND HWANG, G. J., 2015. Interaction between gaming and multistage guiding strategies on students' field trip mobile learning performance and motivation. *British Journal of Educational Technology*.
- [21] ALMUSAYLIM, Z. AND JHANJHI, N. Wireless Pers Commun (2019). <https://doi.org/10.1007/s11277-019-06872-3>.