A Context-Aware Mobile Learning System Using Dynamic Content Adaptation for Personalized Learning

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Abstract. Mobile technologies nowadays contribute to greater options to how learners can enhance their learning styles, leaving behind the traditional learning setup. Indeed mobile learning has become an integral part of our everyday life. Mobile learning refers to the use of mobile devices whereby learning is supported independent of the location and activity of the learner. This learning concept considers continual changes of contexts such as locations and the time available to learn within the mobile environment. Given that the current state of the use of contextual information in mobile learning is not extended, this paper put forward a context aware mobile learning system upon which parameters such as intrinsic and extrinsic context are used in order to improve mobile learning experience of the users. This work aims to synthesize a context-aware mobile learning system using dynamic content adaptation to establish personalized learning contents delivery on portable devices.

Keywords: Mobile learning · Context-awareness · Content adaptation · Personalized-learning

1 Introduction

The rapid proliferation of mobile technology cannot be overlooked. This pervasive technology has brought about considerable changes in the educational sector. The concept of mobile learning is regarded as a tool for students to engage themselves in learning anytime and anywhere. The transparent characteristics of mobile devices have led researchers to focus on its potentials [1]. Hence, the development of quality learning contents to meet the needs of learners is obvious [2].

Context-aware sensing is a key feature of the upcoming technology development, which aims to provide pertinent services and information to end users, based on their situational conditions [3]. Consequently, an attempt to build and deploy efficiently-built context-aware applications using dynamically-generated data obtained from real circumstances raises further investigations. The goal is to develop a resourceful and wiser mobile application without neglecting core features such as contextual data in dynamic environments to bring forward a proactive learning environment.

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This paper introduces a context-aware mobile learning system using dynamic content adaptation for personalized learning. In Sect. 2 some existing mobile learning system is presented. Contextual information and adaptability are discussed in Sect. 3. Section 4 describes the architecture and design of the proposed context-aware mobile system. Section 5 of the paper discusses about the results obtained after evaluating context integration combined with content adaptation. Finally, in Sect. 6 some ideas and improvements are discussed to further enhance the system and Sect. 7 draws some concluding remarks in this area.

2 Mobile Learning Systems

Mobile learning refers to learning which takes place using portable devices while on the move [4]. The ubiquitous mobile technologies are now widely identifiable not only for their portability but also for the use of contextual information to deliver appropriate learning contents [5]. Below are some examples of mobile learning system already implemented and in use by educational outlets.

WizIQ [6] is an educational platform that allows participation in live classes without constraints of time and location. It provides exclusive features like screen sharing and chat to enhance collaboration between students and teachers and notifications of important deadlines, tests and class schedules are made available to users. Open edX [7] is the open-source version of the Massive Open Online Course (MOOC). Based on the learner's previous knowledge, options are made available to choose the preferred topic. However, it is not fully mobile compatible. This is a serious drawback of the application.

Mobl21 [8] is a mobile learning platform that allows for an unstructured way of learning. Layout presentation of the application across various devices is neat and clean. Therefore, focus from the learner is apparent and meets some of the requirements for cognitive maturity. However, limited exploitation is seen regarding repetitiveness of contents or confused statements to extract cognitive maturity at its best. Docebo [9] is a cloud-based, e-learning solution provider which can be accessed through the mobile browser. In addition to providing online contents to learners, tutors can track records of course contents, view progression of learners and manage reports.

3 Context-Awareness and Dynamic Content Adaptation

Context-awareness [10] is any information that can be used to characterize the situation of an entity (person, place or object). Three important characteristics which determine context are where you actually are, who you are with, and what resources are in proximity. A detailed evaluation on context-aware mechanisms to improve cognitive user load showed that technologies requires more work to fully understand human reaction for satisfying interaction [11]. Thus, an investigation on having devices which can sense and acknowledge user context information is essential [11, 12].

A common approach to classify context instances is to distinguish between the context dimensions. These dimensions are referred to as external or extrinsic and internal or intrinsic [11, 13]. External dimensions refer to context that can be measured by hardware sensors such as light, sound, touch, temperature and many others. Internal dimension is specified by the user or captured by monitoring user interactions, such as the learner's goals, tasks to complete and emotional state. Importance is given to external context instances most of the time [11, 14]. Nonetheless, some efforts to use internal context information have been carried out recently [15]. Information about the user himself, his nearby context entities and adaptation to this context is lagging behind. Table 1 classifies context into four main categories.

Table 1. The four main categories of context.

Context category	Description
Learners' context	The learner's identity or a unique identifier from which we can obtain pieces of related information such as user preferences, roles, status, needs, objectives, relationships with peers, and so on
Status or physical context	Properties, which can be perceived by the user. It includes noise level, temperature, lighting, device information, connectivity etc
Time context	Time of the day, day of week, holidays, month, year, date
Location context	Spatial or geographical data. Defines the actual location of the user (in bus, at home, in a public place and so on)

Additionally, context data is important for successful content adaptations in mobile learning systems. Adaptability can be defined as a technique to regenerate a requested content's presentation to adjust to the device capabilities for optimized user experiences [16, 17]. Content adaptations are split into two types which are static and dynamic adaptation. By definition static adaptation pre-processes and stores different versions of the content in contrast to dynamic adaptation where contents are adapted in real-time [18]. Authors [19] stated that there is very little attention on context information and adaptive learning with personalization is missing.

4 Proposed Context-Aware Mobile Learning System (WLP)

In this section, we present a context-aware system, Web-Based Learning Platform (WLP) [20] that adapts the learning contents based on the contexts of the user. To perform content adaptation on the system for personalized learning, two important parameters are considered firstly context-awareness such as the user maturity, cognitive load of the learner and device configuration is used to retrieve context data and secondly content adaptation such as resource, device and network adaptation is accountable for suitable adaptation of the learning materials in the application.

4.1 Context-Awareness

4.1.1 User Maturity

The learners' ages are grouped into three categories (junior, 11–17 years old; adult, 18–45 years old; and senior, 46–65 years old). Junior and senior learners are presented with courses which carries basic explanations while adults are presented with explicitly detailed contents. Seniors are presented with only the essential topics of study as their pace in learning reduces as they grow older.

4.1.2 Device Configuration

Responsive design is one important aspect to consider while designing an application since devices on the market are available in different sizes. The learning materials should adapt to the varied device characteristics. Hence, HTML5, CSS3 and JavaScript languages are used in the system to cater for this change in screen resolution and browser compatibility.

4.1.3 Cognitive Load

In an attempt to encourage learner activities through optimal learning curve, cognitive load is one important factor to consider. The higher the cognitive load, the lower is the user satisfaction in learning [21]. In WLP, short quizzes are provided depending on the learner's age group. Course beginners are provided with simple multiple choice questions with "Yes" or "No" options while intermediate learners are provided with more complex questions with the possibility to choose from four options. The difficulty of the questions, depending on the quiz level and the user age group, is increased after each correct answer given by the learner.

4.2 Content Adaptation

4.2.1 Resource Adaptation

The application checks for CPU and RAM usages to adapt itself in such a way that these resources are used at their optimum level in order to reduce the loading time during the learning sessions. Some 3D content is implemented on WLP which is later tested on different CPU and RAM ranges. The difference in the behavior of the system in accordance of the adaptation levels is noted. Low processor and memory makes contents lag during the loading time whereas using a high processor and memory the content loads flawlessly during user interaction.

4.2.2 Device Adaptation

Device adaptation is one major feature for using diverse platforms such as Android or IOS platform. Besides, browsers are considered so that contents from WLP are presented in the desirable format across varied screen resolutions and browsers.

4.2.3 Network Adaptation

WLP used different bandwidth from cable or WIFI connection to ensure that a constant connection speed is kept when browsing the contents. With an internet speed ranging from 0 kbps to 100 kbps, contents are displayed only as text so that users can learn though at a lower bandwidth while with a speed range of 101 kbps to 250 kbps, content will be textual with some basic images loaded in JPEG format. This will enable users to have some visual content for their learning process. A connection above 1000 kbps (1 Megabyte), results in contents displayed in high definition (HD) quality video (480p or 720p) with textual and pictorial elements. Figure 1 below summarizes the implementation structure of the WLP model.

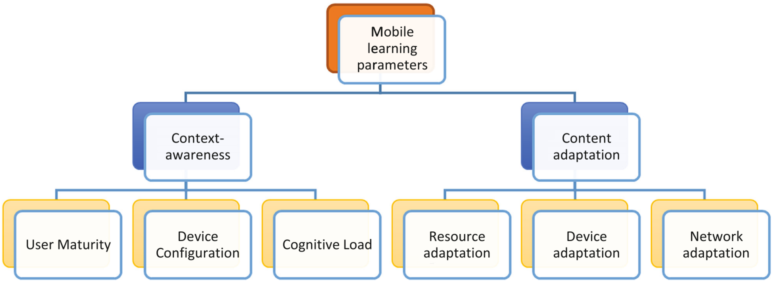

Fig. 1. Implementation structure for the WLP model

4.3 Architecture of WLP

The web system was implemented on PHP's Lavarel Framework and Angular JS by Google. Its data-binding feature allows for automatic updates of views based on changes that occur through the model when a learner interacts with the system. The WLP platform is attached to a database (MySQL) for information storage. Apache is the web server used to control multiple requests made from the devices using context information. Based on the information obtained, a response is delivered to the learner after identifying the devices' specifications in terms of CPU, RAM and browser installed. This will provide for the adaptation of the different contents on the mobile devices. The application is portable on Microsoft Windows, IOS and Android operating systems. A content adaptation mechanism is developed so that users are provided with proper contents during their learning process. Figure 2 represents the architecture of the proposed system.

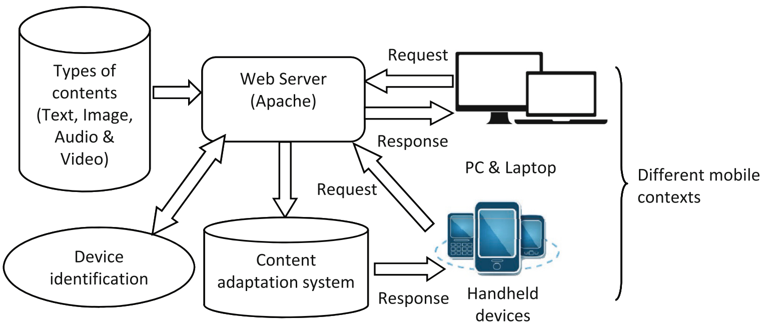

Fig. 2. The system architecture of the WLP

5 Results and Discussions

The learning contents are adapted based on the three age group assumed and defined. A back-end section in the system has been implemented to allow administrator of the application to save contents per age groups as shown in Fig. 3.

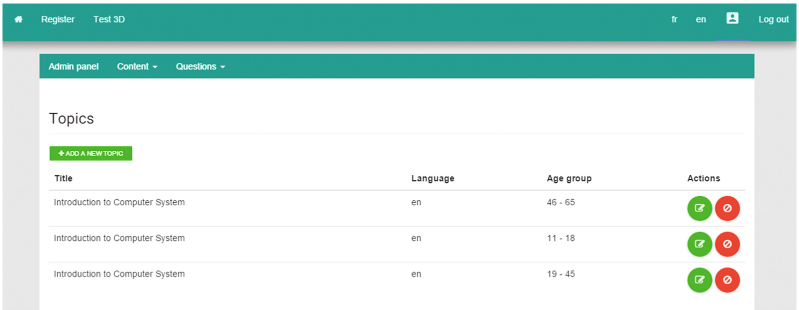

Fig. 3. Different contents saved under the three age groups assumed and defined

Once the user is registered with details including his/her age, he/she is presented with contents appropriate for his/her corresponding maturity. The below screenshot reveals the scenario of a user aged 50. The video loaded is of small length including simple diagrams to transfer the knowledge more conveniently (Fig. 4).

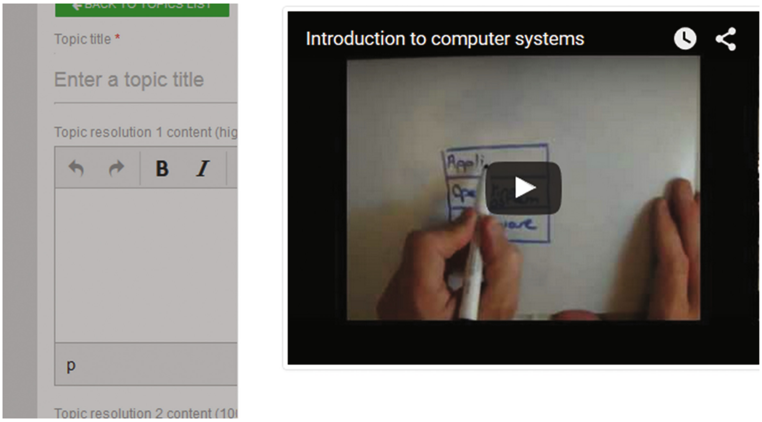

Fig. 4. Short-length video loaded respecting the user maturity factor (50 years of age).

Moreover, the different browsers chosen to test the application revealed good results with WLP. The application loaded with no bugs in its display and thus a fine preview of the contents was made. The layout is well-defined in terms of UX/UI designs and in conformance with W3C standards (Table 2).

Table 2. Device configuration result in WLP

Step	Prerequisite	Expected result	Actual result
1	Application tested on Mozilla Firefox	Application layout to fit perfectly the window	Yes
2	Application tested on Google Chrome	Application layout to fit perfectly the window	Yes
3	Application tested on Safari	Application layout to fit perfectly the window	Yes

The simplicity in the quizzes has been ideally composed per age group and level of study to reduce intrinsic load. In this way, the learner's conscious focus stays on the questions and helps in recalling prior knowledge to provide good answers. Depending on the types of resolutions available through the proposed dynamically adapted resources, the system is accustomed to the delivery of adapted contents based on technical issues such as brightness of screens, speed of video loading, lagging of contents and so on. Good use of media queries was made to acknowledge responsive design of the learning materials. In this way, text contents once appeared larger with only crucial information made visible on smaller-screen devices. The use of wireless communication or cable networks displayed adjusted contents based on the availability of the bandwidth. Table 3 represents the scenarios tested to confirm network adaptability.

Table 3. Network adaptability result in WLP

Step	Prerequisite (connection speed)	Expected result	Actual result
1	78 kbps	Content is displayed only in textual format	Yes
2	110 kbps	Content is displayed both in textual and pictorial format	Yes
3	350 kbps	Content is displayed in textual format and more images are loaded than in previous connection speed	Yes
4	568 kbps	Content is displayed in low quality video (240p or 360p) with text and images	Yes
5	825 kbps	Content is displayed in low quality video (240p or 360p) with text and images	Yes
6	1207 kbps	Video content loaded in standard quality (480p or 720p) with to text and high quality images	Yes

In addition to the network speed, the quality of content streamed should also be dependent on the processor of the mobile device and the current location of the user. Concepts which are very difficult to explain without the use of graphical representation should be made mandatory even in its lower resolutions on low network bandwidth (less than 100 kbps). These are ideas which have not yet been implemented and will definitely contribute to improve the system.

6 Future Works

WLP uses different context information in order to adapt learning contents. Some further evaluation is required to assess the extent of the positive impact on the learner experience. Automatic content adaptation based on the different use cases of user maturity instead of inserting contents manually will be highly in support to a dynamically improved system. Bio sensors can contribute to effective delivery of more personalized data based on the learner's context information. For instance, capturing the eye movement of a user could bring significant amendments while reading. Moreover, the system further needs an in-depth investigation on pedagogical factors such as human behavioral aspects and psychology to reach a higher potential [22]. Related adopted techniques such as the Human Computer Interaction (HCI) or instructional design principles should also be explored. No adaptation is seen based on physical context data such as noise level, light intensity, time and so on. A valid check would be to connect earphones in noisy surroundings while travelling before loading content as audio or video. No detection of earphones would load the contents in text format. The time context can be explicitly defined as per the time of the year. For instance, the amount of information to be tailored during the vacations should focus in reducing the cognitive load for effective study to happen.

7 Conclusion

This paper focused on an adaptive approach to output personalized learning contents by adapting to the learners' context data such as their maturity level and to the resource, device, and network contexts. The dynamic experiments conducted revealed so far a good impact on the user's learning experience. It is obvious that the clear presentation achieved in loading the contents across heterogeneous devices would retain the users' attention and allows good readability. Fluctuations in connectivity often interrupt students from learning. This issue is solved by adapting its contents to the flow in network resources that even with low connection the learner is displayed with adequate amount of information to complete his/her study. A revised version of the WLP may be implemented using additional context information which may result into a more flexible learning lifestyle for students.

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