Mudahnya BM: A Context-Aware Mobile Cloud Learning Application Using Semantic-Based Approach

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Abstract. A great potential of various learning environment in mobile learning application can clearly be seen in current pandemic situation. The accessibility of the learning resources needs to be available from anywhere anytime despite having strong or poor internet connection. It has motivated researchers to imply context-aware capability in improving the accessibility of the learning resources. This paper presents a development process of *Mudahnya BM* mobile application that follows a fundamental concept of Mobile Cloud Learning (MCL). *Mudahnya BM* is an application to learn basic Malay language for learner 7–12 years old. The injection of extrinsic and intrinsic context-aware help the application to improve the reasoning process for finding available learning resources from service providers. Semantic-based approach is applied in the reasoning process. This study involved the end users for evaluation purposes. 33 randomized scenarios have been tested using One-Sample Wilcoxon Signed Rank test. The result shows a positive impact to the population.

Keywords: Context-aware · Mobile cloud learning · Semantic-based approach

1 Introduction

The evolution of education paradigm is based on the evolution of technology. Numbers of mobile applications are developed in accordance with the needs of users. Mobile application needs to serve their content to users by integrating with service providers. This integration helps in diversification of mobile application which will be beneficial to many users through academic, health, work, or online learning activities.

MCL is one of the examples of Service-Based Application (SBA) that has a composition of services in a single application [1]. MCL application is substantial in providing a suitable learning contents where the system itself can track the learner's performance real-time based on the status of learner activities. To ensure that each user receive a correct learning resources, this is where context awareness is considered.

The usage of context aware in MCL has enable the application to aware with the changes of the contextual information such as internet connectivity, device configuration

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status, learner's input, and activities as well as the Quality of Services (QoS). This contextual information needs semantic representation to facilitate in reasoning process [2]. Semantic-based approach has been used in various domain as it has the great potential and ability to provide a meaningful and formal representation of the context as well as the services.

Thus, this resulted in our motivation to devise a context-aware mobile cloud learning application using semantic-based approach. Section 2 presents the background study. Followed by Sect. 3 which discussed the related works. Section 4 shows the design and development processes of *Mudahnya BM*. Section 5 presents the evaluation. While Sect. 6 will conclude the study.

2 Background Study

In general, this section explained on Mobile Cloud Learning (MCL), Context-Aware and Semantic-Based Approach.

2.1 Mobile Cloud Learning (MCL)

Mobile cloud learning term is used when two platforms which are mobile application and cloud computing integrate with each other in education environment [3, 4]. This integration is achieved through network connection. Mobile application will requestion the educational resources from service provider via middleware. In this case, service provider is located in the cloud computing and middleware will be the network bridge between frond-end and back-end.

MCL consists of four main recursive components. Learning, Assessment, Analysis and Feedback are basics components that need to be included in MCL application [3, 5]. The first component in MCL recursive model is the Learning. Learners may access learning resources using their mobile devices which connected to cloud computing. Since learners could be different in their learning preferences from one another, learning resources are delivered to the learners' mobile application based on their current contextual information. Learning component helps learners to prepare themselves by studying the learning materials to make them feel confident during the assessment process.

The second component is the Assessment. Assessment is one of the most important components in MCL. Learners' performance will be analyzed based on the result of the assessment. Learners may self-assess their knowledge level by answering online multiple-choice questions (MCQs) or online quizzes in the subject matter.

Analysis is the third component of MCL model. It comprises statistical analysis of learners learning outcome which is helpful in tracking their learning process. Learners may view their performance based on their assessments result. Their score and their feedbacks are used to develop learning strategy. This strategy is helpful to identify learners' path and their learning contents.

The fourth component is the Feedback. Learners may provide their opinions or recommendations on each of the assessment items or complexity of the learning materials. These feedbacks will be useful for critical analysis on learners' performance which will then be rectified and identified to promote better services in the future. Thus, good quality learning resources will beneficial a larger number of MCL users.

2.2 Context-Aware System

Context can be defined as "… any information that can be used to characterize the current situation on an entity. Entity can be in the form of object, person or place that associate between the system or application" [6]. Contextual information can be further classified into two types which are extrinsic and intrinsic.

External contextual information or extrinsic is normally be acquired using sensor such as sound, light, location, touch, temperature, and others. While intrinsic is the internal contextual information that acquired within the learner prospect such as learner goal, their knowledge background, emotional state, input and interaction, their activities, and others relevant contexts [7].

These two types of contexts can either be static or dynamic. Contextual information can be classified into static of the value of the context does not change over time such as central processing unit (CPU) specification and other. Whereas dynamic context is the context can be changed over time such as status of battery level, network connection strength, date, and time and other.

Thus, the application of contextual information in MCL helps to provide a personalized learning resources to the learners. By leveraging context-aware, it helps MCL become more flexible and allows for adjustments depending on the learners' needs.

2.3 Semantic-Based Approach

There are many approaches offered by current technology to represent contextual information and services (learning resources). One of the promising approaches that broadly used is semantic-based approach. It is implicit approach that semantically provided a comprehensive representation and description of the service and context to support reasoning process during runtime.

Semantic-based approach comprises of six different techniques: Model Driven, Code-Level, Message Interception, Middleware, Rule-Based and Ontology-Based Solution [8, 9]. Based on the hierarchical concept in Fig. 1, ontology-based solution is used to shows the association between the learner and respective contextual information that involved this British Education Ontology [10]. The context as in the figure is categorized into learner and mobile context. Mobile context represents the learning environment and device configuration status, while learning context represents the objective of the learning.

The combination of these techniques can provide better formal representation and expressiveness of the service and contextual information to support reasoning process. Thus, next section will discuss on several research in context aware of MCL that combined these different techniques.

3 Related Works

Some works have introduced extrinsic and intrinsic contextual information in performing adaptation process such as user's location, user's profile, preferred language, device configuration, user's goals, interaction, or time. It is important to mention that most of

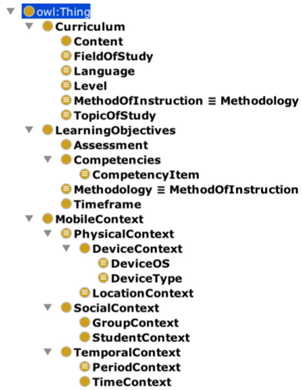


Fig. 1. MCL ontology

these works are followed a fundamental concept of dynamic service adaptation process and MCL recursive model. Ten research in the dynamic service adaptation in context-aware systems using semantic-based approaches were reviewed. The studies are Units of Learning mobile Player (UoLmP) [11], Mobile Semantic Web Assessment Personalization (MobiSWAP) [12], Ubiquitous Learning Framework (ULF) [13], Mobile Response System (MRS) [14], and Web-Based Learning Platform (WLP) [15], Dynamic Adaptation in Context-Aware Mobile Cloud Learning (DACAMoL) [16], Hybrid Recommender System (HRS) [17], Interactive Video-Based M-Learning System (IVB-MLS) [18], Dynamic Mobile Adaptive Learning Content and Format (D-MALCOF) [19] and Context-Aware Mobile Learning System (CAMLS) [20]. The following paragraphs describes all the related works in detail.

UoLmP [11] system is semi-auto adaptation that facilitates students to find available facilitators according to the facilitators' expertise and availability based on input inserted by the students. Adaptability and personalization in mobile learning are referred to the process of fitting the system's functionalities and behavior correspond to the educational goals, location, and movement of the users and well as their learning style [21]. Model-driven approach is used for context modeling that consists of five dimensions which are information, place, artefact, time, and physical condition [22]. Adaptation rules (if/then/else) are considered according to the learner's mobile context dimensions. Apart from that, adaptation algorithms are derived and used such as similarity algorithm, heuristic algorithm, and decision-based algorithm which are processes according to the learner's context dimensions.

MobiSWAP [12] is a mobile application that used semantic-based approach to perform the adaptation process. Contextual information is varied depending on the learner's need in mobile assessment situation. Different learners have their own abilities, profiles, and needs. The framework is divided into three layers which are mobile assessment context layer, semantic layer, and assessment resources layer. The contextual information is acquired from the front layer which is mobile context assessment context layer. The dynamic service adaptation takes places within the middleware layer which is semantic layer. The discovery, ranking, and selection of the services are explicitly stated.

Whereas assessment resources layer is responsible for managing the ontologies, rules, and services.

ULF [13] is developed using selected pedagogical strategies for designing personalized learning path. The framework consists of Adaptation Layer, Adaptation layer, and Personal Data Locker (PDL). Presentation layer is responsible to support the understanding the content of PDL reasoning process. Adaptation Layer comprises of rules for selecting both concept and content for learning path. Learning goals integrated with domain ontology are for sharing knowledge purposes.

MRS [14] facilitates in-class interactive problem solving using mobile devices. MRS is designed as a three-tier architecture. MRS client would gather as much contextual information from the user side as possible such as device's battery level and internet connection. Whereas cloud IaaS (Infrastructure as a Service) is used as a middleware to facilitate dynamic service adaptation that act as a broker between the clients and the server. IaaS is used to minimize the instructor's workload. Thus, it helps students to have transparent access and enables the system to be extensible to any disciplines. This system automatically prompts the students' devices to do exercises that synchronize with lecturers' materials. Hence, students will actively interact by providing feedback, question, or vote to existing pool to lecturer since MRS supports anonymous communication and MRS also provides analysis on students' performance.

WLP [15] adapts learning contents according to the learner's contexts. WLP acquire their contextual information from web-based application and mobile-based application. The dynamic service adaptation is operated within the web server. Rule-based approach for content adaptation is performed based on two parameters which are (i) context awareness such as user maturity, device configuration, and cognitive load of the learner, and (ii) content adaptation such as network, device, and resource adaptation.

DACAMoL [16] is a framework developed for MCL environment that provides personalized learning resources to the learner's according to device context and learner context such as network status, device battery level, learner's input, and learner's profile. These contexts help in reasoning process to provide correct and effective services to the learner. Ontology-based and rule-based approaches are used in the framework via Semantic Web Ontology Language (OWLS) technology.

HRS [17] adapts it learning contents according to learner's contextual information such as learning goals, knowledge level and sequential access patterns. Hybrid approach using sequential pattern mining (SPM) and CF algorithm help to improve the reasoning process. Contextual information and services are represented using model driven approach as well as ontology-based solution. HRS provides self-adaptation process help to improve the QoS and accuracy of the service substitution.

IVB-MLS [18] implies a self-adaptive smart learning environment that provides streaming video as well as prerecorded lecture session to the students. The video is served to the students according to mobile device contexts as well as students' contexts such as network transmission, mobile device type, learners' profile as well as learners' activity. The framework used the combination of approaches which are code level, message interception and model driven. Real-Time Transport Protocol (RTP) technology is used in the system.

D-MALCOF [19] is a mobile learning system that facilitates students to improve their learning skills. This framework can detect knowledge level of the learner, learner's profile, and their learning style through different sensors. Hence, the system will provide a suitable learning style to respective students according to their contextual information. Model driven approach, middleware and rule-based solution has been used for the reasoning process via Simple Object Access Protocol (SOAP) technology.

CAMLS [20] is a mobile learning system provide a comprehensive system to the students and lecturers to keep updating about current state of the system that they used. Thus, they will be aware about what is happening during the interactions. Users can have full control over the system which helps to motivate users in teaching and learning aspect. Contextual information such as learner profile, their activity and disabilities are acquired to provide real time services via augmented reality environment.

Based on these findings, to develop context aware MCL application, self-automation is substantial as it will remove the interruption while learner uses the application. It also enables the application to continuously monitor the context changes during run-time and provide correct learning resources to the learner. Whereas the semantic-based approach should be combined within the technique for better service and context representation.

4 Design and Development

Developing a mobile application must follows fundamental knowledge of the chosen domain. MCL recursive model is the main guideline for developing *Mudahnya BM* mobile application. Figure 2 shows the low-level UML component diagram of the application. Three main components involved are the device or mobile application itself, web server and service provider.

Users interact with the application via the device component. Six different component that integrate with the users are Learning, Assessment, Feedback, Performance, QoS and DeviceStatus. Each of these components required the input from the sensor or user and provide their output to the web server as a reasoning mechanism.

This is where extrinsic and intrinsic contexts are acquired such as (Extrinsic: network status, device battery status) and (Intrinsic: learner profile, learner input, QoS). Since *Mudahnya BM* is a real-time application, the contextual information will change over time.

The contextual information is then passed to the web server component in the web server via Hypertext Transfer Protocol (HTTP) request using Representational State Transfer (RESTful) web service. DACAMoL web service will become as a controller that transform the context using ontology semantically. Rule-based techniques is also used to discover the available learning resources from service provider.

DACAMoL web service will discover the available services from service provider. Service provider will bind their service when the request meet the equivalence service that they have. There are three main services stored in service provider which are: (1: Service with image, 2: Service with grey out image, 3: Service without image).

These three services will be served according to the contextual information. Based on the list of rules in Table 1, the three main rules are; Rule 1 (i.e. service discovery rule), Rule 2 (i.e. service ranking rule), Rule 3 (i.e. service binding rule).

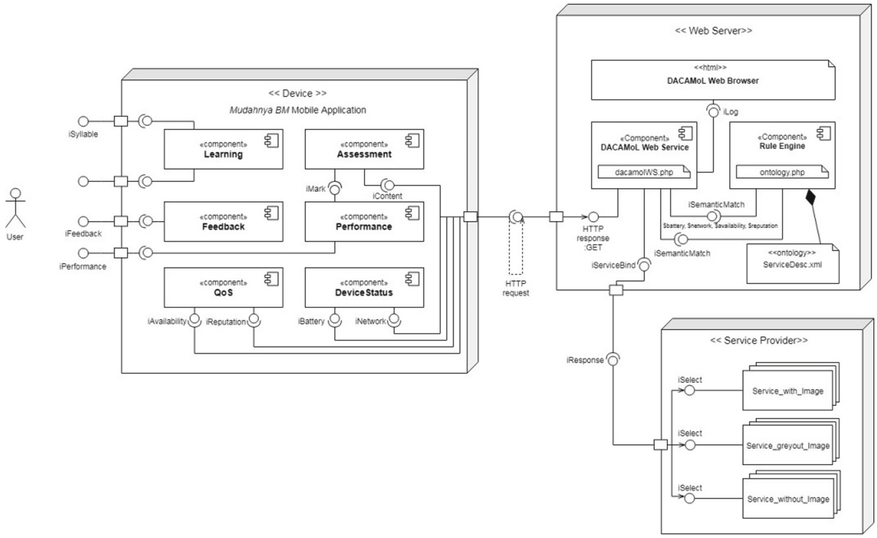


Fig. 2. Low-level component diagram of *Mudahnya BM*

As stated in Rule 1.3 and Rule 1.4b from Table 1, network status is categorized into two different scales which are poor and strong. Network is considered as poor if it is 66 kilobits per second (Kbps) and below. Higher than this value is considered as strong network. Whereas battery level is considered as low if the value is 49% and below [23].

As for selecting the services, availability is the higher priority ranking where the services should be in available state that score 98% or higher. Reputation on the other hand is defined as a rating of the service from user in a specific period which is an important factor for users to select the best service among many services. Scores of 1, 2 and 3 is considered low while 4 and 5 is considered as high score.

The screenshot of the application is shown in Fig. 3. The screenshot is captured from assessment module where it comprises of three different level. Figure 3 shows the lowest level which is level 1.

Learner needs to answer what would be the small letter for the question. For example, learner needs to find what will be the small letter for capital B. There user interface will be based on the context changes. If the network connection is strong, device battery level is optimum, QoS is high, thus learner will receive color image. If some of the contexts are not in the optimum value, grey out image will be provided. If each context is in its lowest value, only textual information will be displayed.

5 The Evaluation

The objective of this evaluation is to measure the correctness of the chosen learning resources based on the context changes and QoS. The correct application is correct if it exhibits the correct services for all correct scenarios. Thus, the correctness of *Mudahnya* BM is based on the number of correct scenarios which must correct more than 32 scenarios out of 33 scenarios. This is because 32 is represent 95% of the population.

Table. 1. List of rules

Rule	Description
Rule 1: Service Discovery	Rule 1 uses to discover available services based on context changes from learner or device such as learner's age, mark, network status, or battery level.
Rule 1.1	Age = 7, 8, 9,10, 11, 12 If Age = 7 | 8 | 9 | 10 | 11 | 12 Then Service = [Learning_Resources]
Rule 1.2	Mark = 0 to 100 If 0 ≤ Mark ≤ 100 Then Service = [Assessment Level 1] else if 80 ≤ Mark Level 1≤ 100 Then Service = [Assessment Level 1, Level 2] else if 80 ≤ Mark Level 2≤ 100 Then Service = [Assessment Level 1, Level 2, Level 3]
Rule 1.3	Network = strong connection or poor connection If Network_strong ≥ 67 Kbps Then Service = [Assessment Level 1, Level 2, Level 3 with color image] else If Network_poor ≤ 66 Kbps Then Service = [Assessment Level 1, Level 2, Level 3 greyed out image/ textual]
Rule 1.4	Rule related to battery level of the device
Rule 1.4a	int contextValue = getContext (LowContext) if X == contextValue(true) { HighContext = convertContext} Return HighContext
Rule 1.4b	If HighContext ≥ 50% Then Service = [Assessment Level 1, Level 2, Level 3 with color image] else Then Service = [Assessment Level 1, Level 2, Level 3 greyed out image/ textual]
Rule 2: Service Rank	Rule 2 uses to rank the service from service candidate according to QoS values

Rule 2.1	If (QoSValue_Availability ≥ 98%) && (4 ≤ QoSValue_Reputation ≤ 5)
	Then Service = [Assessment Level 1, Level 2, Level 3 with color image]
	else
	Then Service = [Assessment Level 1, Level 2, Level 3 greyed out image/ textual]

Rule 3: Service Binding	Rule 3 uses to enact the adaptation
Rule 3.1	If Rule2.1 success Then Service = [Assessment Level 1, Level 2, Level 3]

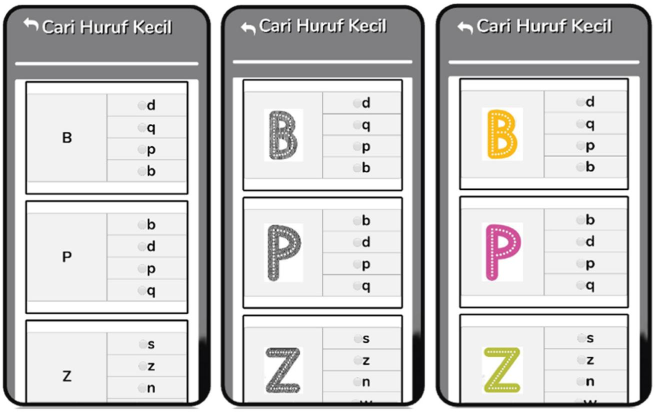


Fig. 3. Screenshot of *Mudahnya BM*

The 33 scenarios are separated into six subcategories. These subcategories have been clearly justified which are based on the probability that might arise during runtime such as the combination between high battery level (≥50%), high internet network (≥67 Kbps), high QoS in availability (≥98%), high QoS in service reputation (≥4). These data can be varied among participant in term of their context changes. Sometimes the battery level can be low, but the internet connection is high, and they might be charging their phone or unplugged the charger. We have simulated these scenarios to cover each 33 scenarios during runtime since it is impossible to control the battery level and the internet network connection.

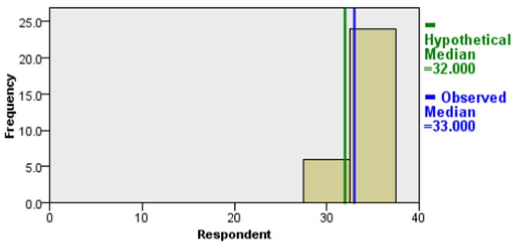
After the pilot study was approved by the expert reviewers, the experiment with real participants was conducted. This evaluation is a Quasi-experiment where we prior selected 30 Software Engineering third years' students from Universiti Putra Malaysia. They should be skilled in SOA, service adaptation and able to understand Malay language since *Mudahnya* BM mobile application is in Malay language. They must own an Android-based mobile device, or they will be provided with a device if they do not own any device for the purpose of this evaluation. Next, they must install *Mudahnya* BM mobile application in their mobile devices. The participants need to run the application and monitor from time to time and answer the checklist according to the stated scenarios.

Based on the result from 30 participants (N = 30), they managed to score 30 and above. 80% of participant manage to get all correct scenarios which are 24 participants. While five participants only received 32 correct scenarios which is 17%. At least only one participant received 31 correct scenarios which is 3%.

Two hypotheses are deduced prior the evaluation which are: -

1: *Null Hypothesis* (H_0): $m \leq 32$
2: *Alternative Hypothesis* (H_1): $m > 32$
m = median

Since the median of this evaluation is 33, the null hypothesis can be rejected Since Shapiro-Wilk normality test is less than 0.05, a further statistical test which is Wilcoxon Signed Rank test is conducted to verify the correctness of the application.



Total N	30
Test Statistic	312.000
Standard Error	32.500
Standardized Test Statistic	4.600
Asymptotic Sig. (2-sided test)	.000

Fig. 4. Wilcoxon signed rank test result

Based on the result from Fig. 4, 4.600 Standardized Test Statistic resulting 0.00 for the p-value of Asymptotic Sig (2-sided test). The bar graph illustrates the observed median which is 33 is higher than the hypothetical median; 32 value that priorly been set up. Null hypothesis can be rejected since $m \leq 32$. The objective of the study achieved.

6 Conclusion

This paper has presented a study on context-aware mobile cloud learning using semantic based approach. A mobile application called Mudahnya BM is developed based on the background study of related works and follows fundamental concept of MCL. The correctness of the adapted learning resources is verified based on the evaluation within the end user. To conclude, a specific contextual information might affect the correctness of the application which will promote better learning experience to the users. As for the future work, different contextual information might be considered as well as different approach such as machine learning might me combined with the current method which is semantic-based approach.

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