A context-aware personalized m-learning application based on m-learning preferences

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Abstract

The purpose of this paper is to present the data analysis obtained from our interview study, which showed that participants had different individual mobile learning (hereafter, abbreviated as m-learning) preferences. The understanding of these preferences for different m-learning requirements can be used as a foundation for building successful personalized m-learning applications catered to learners' individual m-learning needs. Participants' dynamic m-learning preferences (including location of study, noise/distractions level in a location, and time of day) are described. We propose a context-aware personalized m-learning application based on these m-learning preferences. Six scenarios are given to illustrate the m-learning preferences of different learners. The system architecture consists of a learner profile, personalization mechanism and learning objects repository. An initial m-learning preferences questionnaire is used to obtain learners' dynamic m-learning preferences. Current context values are retrieved from context-aware technologies. Appropriate learning objects are selected to learners based on their preferences and context values.

1. Introduction

M-learning was defined by O'Malley *et al.* [1] from the pedagogical perspective as "*any sort of learning that happens when the learner is not at a fixed, predetermined location, or learning that happens when the learner takes advantage of learning opportunities offered by mobile technologies*". The first part of this definition implies that any type of learning that takes place with or without mobile devices can be classed as m-learning, where fixed locations may include computer laboratories, libraries and lecture theatres. In this sense, m-learning is not necessarily an exclusive property of mobile technology, rather it is the mobility of the learner who during their everyday life moves from one situation to another, being in different locations, with different social groups, using different portable and non-portable technologies and learning different topics [1]. Under these circumstances, the following examples would also constitute m-learning.

- Language students studying/improving their language skills whilst at home or abroad.
- Students reading paper-based lecture notes on the bus to the university.
- Nurses or doctors accessing/updating their medical knowledge on hospital grounds using medical books.

The same view is shared by Becking *et al*. [2] who defined m-learning as a learning process in which a learner has the time and is willing to learn either alone or in a group, with or without mobile devices.

Learning preferences may comprise of *learning styles* (students' preferred styles of learning), *learning strategies* (students' preferred strategies of learning such as deep, surface or strategic) and *learning characteristics* (related to the personality of a learner and how these may affect the way they prefer to learn. These characteristics may include levels of motivation, background, strengths and weaknesses, interests, ambitions, and sense of responsibility. For example, a conscientious learner may want more detailed learning materials than a non-conscientious learner.

The use of learning styles for the personalization of web-based learning and m-learning applications have been developed by researchers including Kinshuk and Lin [3] and Park [4] respectively. A learning style was defined as a "*description of the attitudes and behaviors that determine our preferred way of learning*" [5]. The Felder and Silverman learning styles model [6] is one which distinguishes learning preferences of learners based on four dimensions – 1) active/reflective, 2) sensing/intuitive, 3) visual/verbal, and 4) sequential/global. This model is frequently used for

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modeling learning styles within personalized learning applications for adapting or selecting learning content to learners, such as in Park [4], Graf and Kinshuk [7,8].

Many current and/or existing context-aware or context-based m-learning applications utilize what are known as learning contexts in order to appropriately adapt or suggest learning content/activities to learners. A learning context is defined as "*the circumstances in which, or conditions that surrounds the learning*" [9]. These are usually dynamic entities relating to a learner which are developed when learning 'on the move' i.e. m-learning [10]. Prekop and Burnet [11] divided learning contexts into two dimensions - internal (which surrounds the user) and external (which surrounds the application). A literature review of context-aware m-learning applications deploying different contexts using various mobile and context-aware technologies was provided in [12].

Static learners' learning preferences and dynamic learning contexts have been made use of within web-based learning and m-learning applications. However, the use of static m-learning preferences relating to learning on mobile devices and/or in mobile environments has not been explored extensively. Establishment of such preferences can be used to build successful personalized m-learning applications based on individual static m-learning preferences.

In this paper, we focus our discussion on our interview study findings relating to learners' m-learning preferences. This interview study was primarily conducted to establish the m-learning requirements of intended users relating to our mobile context-aware learning schedule (mCALS) framework. The framework was described in [13] and the interview study methodology and extensive data analysis relating to the framework were presented in [14,15].

The main results presented established a) four types of usual studying environments participants used – study-dedicated, home areas, café areas and transport, b) whether learners currently make use of any paper-based and/or electronic-based learning schedules for time management of their studies, c) which learning contexts are important for the consideration in the suggestion of learning materials to students, and d) which types of learning materials may be appropriate for learners under which circumstances.

Additional data was collected from participants during the interviews, which indirectly related to our mCALS framework. Further analysis of these results informs us that a) many of the participants had different m-learning preferences (including location of study, perceived distractions within a location, and time of day); b) they were aware of their m-learning preferences, if any. We use these obtained m-learning preferences to construct a personalized m-learning application to cater for the needs of individual learners.

The structure of the paper is as follows. A literature review relating to m-learning is provided in section 2. Our interview study research methodology and data analysis relating to learners' m-learning preferences are presented in section 3. Scenarios and system architecture of our proposed personalized m-learning application are presented in section 4. Finally, conclusions and future work are presented in section 5.

2. Literature review

We provide a literature review relating to two aspects of m-learning – a) the relationship between the Dunn and Dunn learning styles model [16] and m-learning itself, and b) 'learning objects' and the 'Mobile Learning Metadata' [10].

The Dunn and Dunn model [16] contains various components within five categories - *environmental, emotional, physical, sociology and personality* - which describe a wide range of learning styles/preferences a learner may have. Relationship mappings between the components of this model against the context space [17] and categories of contexts [18] were previously established in [19,20]. A summary of the relationship mappings given in [15] suggest these as pedagogical guidelines and/or considerations for developing m-learning applications is as follows.

- Learners may have preferences to study in different locations with different noise levels.
- Learners may have varying levels of motivation and degrees of responsibility for their learning.
- Learners may have different learning preferences and their performance in learning/studying may be dependent on the time of day and how mobile they feel.
- Learners may have preferences to study alone, together with peers, or in a learning group.
- Learners may have varying levels of attention and they may be affected more easily when they are performing m-learning. This is potentially due to the increased noise levels, movement, interruptions and distractions.

The Mobile Learning Metadata (MLM) [10] was extended from the Learning Object Metadata (LOM) [21]. Learning objects are defined as learning materials which can be used, reused, or referenced during web-based learning [21]. LOM [21] is an international standard which is used to describe learning objects so that these can be stored, searched and retrieved efficiently. It contains nine categories - *General, Lifecycle, Meta-metadata, Technical, Educational, Rights, Relations, Annotation* and *Classification.*

Additional metadata tags can be added to the LOM specification [21]. The purpose of the construction of MLM [10] was to facilitate the storage, searching and retrieval of m-learning objects to fit the criteria of m-learning students. The MLM specification [10] comprises of 3 top level classifications – Learning Object, Learner and Settings (describes the context state of the learning environment such as the location of the learner or learning object). The Learner classification is then divided into two sub-categories – *Learner Profile* (contains static information about the learner and their preferences) and *Learner Model* (contains dynamic information relating to the learner's knowledge and learning history.

Conceptually, the relevant learning object is located by the context-aware engine of an m-learning system using the information provided by the Learner and Setting classifications by accessing the metadata of the learning object. Information within the Setting classification is generation dynamically to describe current values of context information.

3. Interview study and data analysis

In this section, we first provide a brief description of the interview study research methodology including the deployed data analysis method, structure and limitations of the study; note that these were extensively described in Yau and Joy [14,15]. We present our data analysis of m-learning preferences relating to the location of study, perceived distractions within a location, and time of day in the sub-sections that follow.

3.1. Research methodology

37 university students participated in our study, on a one-to-one basis, with a single researcher. The interviews were recorded and then transcribed for data analysis. Consent was given by all volunteers to agree on participating in the study. The average duration of each interview was approximately 27 minutes.

The data sample included 17 computer science students, 7 business studies, 6 mathematics, 2 engineering, 1 physics, 1 law, 1 history, 1 industrial relations and 1 European cultural policy. 24 were undergraduates and 13 were postgraduates. 32 were students from our university, and 5 were recruited from the University of Nottingham. Responses from participants had started to recur after we had conducted around 30 interviews with participants. At that stage, we decided that further interviews would not assist us in obtaining much further information. We also had time and resources constraints. Therefore, our study ended after the interview with the 37th participant.

We had employed the content data analysis method [22] for the qualitative analysis of our interview study due to its pedagogical and exploratory nature. This data analysis method allow a) categories of results findings to be emerged from the interview raw data; b) responses from participants for each interview question to be grouped together to enable categories to be emerged from the grouped responses; and c) further analysis to be conducted on the responses [22].

Our interview study was structured into four coherent topics and contained collectively 30 interview questions under four topics – *studying in various locations, learning preferences, use of learning schedules* and *learning contexts*. In addition, a brief questionnaire/checklist was given to participants to complete at the end of the interview.

The questionnaire presented participants with a list of factors which they were to indicate on a scale of 1 to 5 (1 being least significant and 5 being most significant) the significance of each of the factors in affecting their concentration for studying. These factors (derived from [16]) included *noise level, temperature, lighting level, their seat, layout of room, type of location, motivation, how responsible they feel towards their studies, their persistence in learning, how organized they are, their learning preferences, food and drink, time of day, how free they feel, whether they are working alone/peers, motivation from their teacher/lecturer* and *how anxious/depressed they feel*.

The data analysis presented in this paper is focused on the data obtained from the first two interview topics and the questionnaire/checklist.

Limitations of our interview study (described in [14,15]) include – 1) the sample size of 37 university students from the universities of Warwick and Nottingham, UK, may not be represented of university students in general; 2) participants are required to have a sufficient level and maturity of understanding, reflection and ability in order to convey their learning preferences and experiences to us; this level and maturity may vary between different participants.

3.2. Preferences for a location of study

Previous data analysis conducted and presented in [14,15] showed that four typical locations of study were utilized by participants – *study-dedicated areas, home areas, cafes* and *transport*, and the reasons for the utilization. Precise individual preferred locations of study are presented here. 25 of the 37 participants had the following preferred locations for studying.

- 14 participants' study locations included home and library.
- 5 participants' study locations included home and office.
- 4 participants' study location included home.
- 2 participants' study locations included home and computer laboratory.

The following locations of study were preferred by each of the remaining 12 participants, respectively.

- Office
- Home, library, learning grid, café
- Learning grid and computer laboratory
- Home and quiet rooms on campus
- Only communal spaces of home and computer laboratory
- Library, computer laboratory and train
- Home, computer laboratory and learning grid
- Home, library and learning grid
- Home, library and corridors between lectures
- Student lounge
- Home, library, computer laboratory, learning grid, student lounge
- Home, biology laboratory and office

Insights gained from the interviews and data analysis revealed that not only that the participants had one (or more) preferred locations or types of locations for studying, there may also be specified locations in which a participant would not study in i.e. not preferred locations of study (due to low levels of productivity). Moreover, there were several instances where participants had informed us their preferred and not preferred locations which were the complete opposite of those of other participants. For example, one may find the library to be very effective for them to study in, whereas another cannot usually concentrate at all there. Similarly, one participant may only be able to study at home whereas another is not able to study there.

This finding informs us a generic m-learning application, for example, one that uses appropriate suggestion rules to select learning materials to students based on their location of study. Such suggestion rules may specify for example 1) a learner is to undertake materials which require high levels of concentration and is to be conducted in the library, and 2) a learner is to undertake materials which require lower levels of concentration in a café area. Whereas for some students this suggestion and undertaking of materials is appropriate for them in the mentioned locations because they can concentrate better in the library than in the café area. Our data analysis showed that for other types of learners, this may not always hold true.

3.3. Preferences for perceived distractions within locations of study

Our data analysis showed that learners' preferred locations are related to the distractions (whether real or perceived) in the location. Hence, the decision for choosing a location of study is usually based on the real or perceived distractions in the location. Participants were asked to inform us the factors in a location that had potential/ability to decrease their concentration from their studying task. A list of factors were obtained and were first presented in Yau and Joy [14,15]. These factors were *noise, busyness of the environment, temperature, light, layout of the room, their motivation,* and *urgency of the task*. Food and drink, and time of day were also mentioned.

We used these factors as the basis of our diary study which was conducted partially to ascertain which factors (or learning contexts) can have a strong positive or negative effect on the student's concentration level. Our diary study research methodology and its results were detailed in [12]. 'Diary entry' sheets were specially designed for this study for participants to indicate the values of the factors - *noise, busyness of the environment, temperature, motivation, urgency of task, frequency of interruption* and *their concentration level throughout the session* on a scale of 1-5 in each of their learning sessions. For example for noise level, 1 represented least noisy and 5 represented most noisy.

157 'diary entry' sheets were completed and we used these to calculate the correlations. The results obtained show that there was a strong negative correlation between the noise level and the learner's concentration level, and a strong positive correlation between the motivation level of a learner and their concentration level. These findings suggest that, in general, the higher the noise level, the more negative impact it has on the learner's concentration level whereas the higher the motivation, the more positive impact it has on the learner's concentration.

A number of participants had the same preferred locations of study. However, the distractions (perceived or real) in these locations may not be the same. Similarly, although general trends were found amongst participants that certain factors can cause strong positive or negative impact on their concentration level, the interview study results inform us that each learner may have their own preferred value of factor/learning context. For example, a learner may prefer a certain level of noise. Table 1 summarizes the results obtained from our interview checklist of the 37 participants, showing also that students had the opinion that their motivation had the most significance towards their concentration.

Table 1 – Significances of factors

FACTORS	5	4	3	2	1
Noise level	13	13	7	3	1
Temperature	3	15	12	6	1
Lighting level	3	9	9	14	2
Your seat	2	10	13	11	1
Layout of room	0	4	8	12	13
Type of location	9	17	9	2	0
Motivation	26	7	3	1	0
Responsibility	6	14	14	1	2
Persistence	4	17	14	2	0
How organized	3	16	13	5	0
Preferences	6	13	12	5	1
Food and drink	9	8	7	12	1
Time of day	3	13	14	6	1
Free/restricted	3	12	15	3	4
Working alone	6	8	17	2	4
With peers	3	10	16	4	4
Motivation[1]	3	4	12	12	6
How anxious	6	15	10	5	1

[1] From teacher or lecturer

3.4. Preferences for the time of day to study

We asked participants if they had any preferences for the time of the day for studying. Participants' preferred time of study are as follows. Note that most students were aware of when they studied best and most productive. 4 participants noted that they had no time preferences for studying.

- Mornings – 7 participants
- Daytime (including mornings) – 7 participants
- Mornings and evenings – 2 participants (An example was given by a participant: they can memorize better in the mornings, and do other types of work better in the evenings).
- Afternoon – 4 participants
- 12pm to 12am – 1 participant
- Nights and evenings – 12 participants

4. A personalized m-learning application based on m-learning preferences

In this section, we first describe six scenarios of students with different m-learning preferences, followed by the system architecture consisting of 3 components – *learner profile, personalization mechanism* and *learning objects repository*. Finally, we provide a discussion of related work and applications.

4.1. Scenarios

Six scenarios are given below to illustrate the different m-learning preferences of six different types of mobile learners. The scenarios distinguish between different learners' preferred locations of study, their preferences for the levels of noise/distractions in a location, and how strongly they feel towards these preferences. In addition, each student described may prefer a different time of day to conduct their studies.

- Student A has strong preferences to study in quiet environments and can concentrate best when there are no distractions. His most preferred location of study is the library.
- Student B has strong preferences to study in noisy environments and can only concentrate when it is noisy and/or there are people around. His most preferred locations of study include student lounges and cafes. (This may possibly constitute a minority of students.)
- Student C has medium preferences to study in quiet environments although he can

concentrate in noisier ones. His preferred study location includes computer laboratory.

- Student D has medium preferences to study in noisy environments although he can also concentrate in quieter environments. His preferred location of study is the library café.
- Student E has weak preferences to study in quiet environments and can concentrate on his studies in most locations.
- Student F has weak preferences to study in noisy environments and can concentrate on his studies in most locations.

4.2. System architecture

Our proposed personalized m-learning application based on m-learning preferences consists of three components - 1), a learner profile for storing m-learning preferences, 2) a personalization mechanism, and 3) a learning objects repository. Techniques (including context-aware technologies) are used to automatically detect the values of surroundings to retrieve the current location, noise level, and time of day. These values are used to determine which learning materials are appropriate to the student taking into account their individual m-learning preferences. Figure 1 illustrates the system architecture.

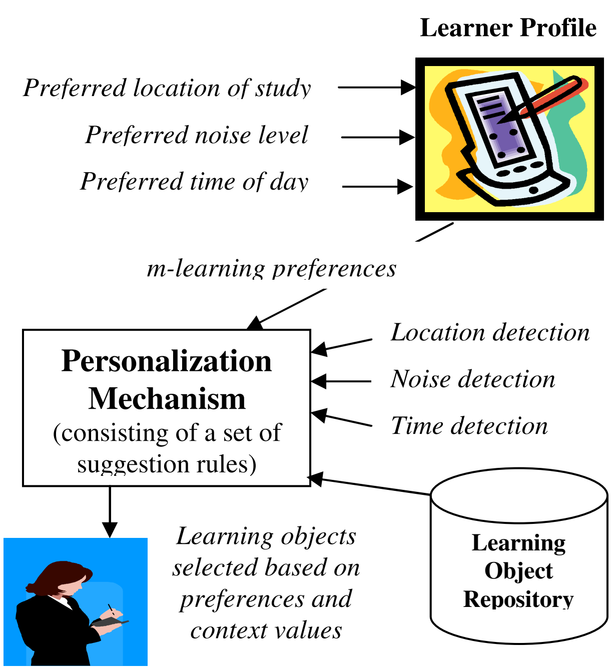

Figure 1 - System architecture and components

Learner Profile

The learner profile consists of an initial simple m-learning preferences questionnaire, which is generated for students to input their m-learning preferences on a one-time basis before the user commences with their learning activities and are stored into the application. Data analysis showed that m-learning preferences of participants were usually static and fixed. However, there is always likelihood that these are subject to change. Therefore, our application allows the option for users to change their preferences, if they wish to.

Three preferences are to be inputted to the application – *location of study, level of noise/distractions, time of day* – together with how strongly students felt towards these preferences (strong, medium or weak). Such an m-learning preferences questionnaire is similar to the existing learning preferences/styles questionnaires, for example Felder and Silverman [6] and Honey [5], to applications to find out the learning styles of students prior the use of web-based or m-learning applications. At present, we are not aware of any m-learning preferences questionnaire being researched or deployed.

Personalization mechanism

The personalization mechanism has two inputs, a set of suggestion rules for personalization and an output of appropriate learning objects retrieved from the learning object repository for learners to learn/study.

The inputs include the learner's m-learning preferences and the current values detected by the context-aware technologies. We first describe how the latter are retrieved. The learner's current location can be detected using GPS technologies (for outdoors) and Wireless LAN positioning technique (for indoors and outdoors); the latter technique uses the retrieved signals from the wireless network being accessed to imply the location of the learner by the access point or station they are connected to [23]. The level of noise can be detected using a microphone built-in or attached to the mobile device being used. The current time of day can be easily obtained from the device's internal clock.

Potential suggestion rules for the suggestion of appropriate learning objects to learners based on their m-learning preferences can be constructed by matching the metadata of learning objects to the current values of the location, noise/distractions level, and time of day. M-learning preferences should also be taken into account. For example, if the learner concentrates well in noisy environments, then a learning object requiring a higher level of concentration can be suggested to a learner. Whereas, if another learner can only concentrate well in quiet environments, then a learning object requiring much lower levels of concentration can be suggested to the learner in the same noisy environment.

Learning objects repository

We have chosen a Java learning object repository such as www.codewitz.org for providing us with the Java learning objects required for this application. We decided the use of Java learning materials are appropriate for our application because large amounts of time and motivation are required to learn an object-oriented programming language such as Java, and we are currently seeking ways to facilitate this for novice programmers.

4.3 Related work and applications

In this section, we provide a review of current personalized and/or context-aware m-learning applications related to our work, as follows. Note that the difference between context-aware and context-based is that the contexts are retrieved automatically from context-aware technologies in such an application whereas in context-based applications, the contexts are usually retrieved from the user via an interactive request method via input [15].

The context-based English tenses m-learning application [24] considers the learner's concentration level, frequency of interruption, available time contexts as well as their user model for selecting appropriate English tenses to them, at the location of their study.

The context-aware English vocabulary learning application [25] considers three internal and external contexts of learners including learner's location, leisure learning time (i.e. time of day) and individual abilities. The aim of this is to increase the learner's interests in language learning and enhance their ability and performance in using and practicing the language with people. For example, Christmas vocabulary is displayed to the student when the date is December 25, and food/drinks vocabulary is displayed to the student if they are in a restaurant.

The CLUE knowledge-awareness application [26] enables collaborative learning between learners. It makes use of two community contexts – the leaner and other learners surrounding them – in order to facilitate the learning process. The application is particularly aimed at distance learners for helping them to identify which learners are situated around them and what they know about different subjects/topics. This information is geographically displayed in a knowledge awareness map to enable them to seek help from one another and to find collaborative peers to learn/study with.

An adaptive personalized recommendation model for recommending SCORM-compliant learning objects from online learning object repositories was constructed by Wang *et al*. [27]. The learner's intention and preferences are considered in order to select relevant learning objects to them. Sharable Courseware Object Reference Model (SCORM) [28] is an international standard proposed by Advanced Distributed Learning initiative (ADL) for solving the problems of sharing and reusing learning materials in different and incompatible formats of web-based learning systems.

5. Conclusions and future work

In this paper, we have presented the data analysis from our interview study relating to the individual m-learning preferences of learners including their preferred location of study, noise/distractions level and time of day. We proposed a personalized context-aware m-learning application based on these m-learning preferences. This application has the potential for motivating learners to learn/study in different m-learning environments as their individual m-learning requirements are taken into consideration.

The system architecture and components of this application was illustrated and described. Firstly, a learner profile requests the m-learning preferences from learners and stores these. The personalized mechanism then considers these m-learning preferences of the learner together with the current context values retrieved from context-aware technologies (including GPS, Wireless LAN technologies and microphone for detecting the location and noise level). The time of day is detected by the internal clock of the mobile device. Appropriate learning objects are selected to the learner based on these considerations.

Future work includes 1) construction of more precise suggestion rules for the personalization mechanism in order to accommodate the needs of individual mobile learners; 2) software implementation of the application using mobile and context-aware technologies; 3) evaluation of the software application to take place with students; 4) consideration of the findings critique from learning style models such as Dunn and Dunn [16] and Felder and Silverman [6]; and 5) consideration of Vincente's Cognitive Work Analysis [29] which may be a supplementary approach for analyzing human-technology design issues.

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