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Personalized Mobile Learning and Course Recommendation System

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ABSTRACT

Mobile-based learning provides new experience to the learners to learn anything from anywhere and anytime by using their portable or mobile device. Vast educational contents and also different media formats can be supported by the mobile devices. Access speed of those materials has also improved a lot. With this advancement, providing required content or materials in the desired format to the learner is essential to the learning management system. Also, it is very important to guide the learner based on their interest in learning. With this outset, the proposed mobile learning system helps the learners to access different courses under different levels and different specializations. The course contents are in different formats called learning objects (LO). In order to provide personalized learning experience to the learner, the system finds the learner's preferences and selects the desired learning objects. It also recommends some specializations with level to the learners to achieve higher grades.

KEYWORDS

Classification, Mobile Learning, Personalized Learning

INTRODUCTION

Usage rate of mobile phones increased tremendously in the past few years and it creates new way for learning that breaks the boundaries of conventional classroom-based teaching-learning method; hence the learners can learn anything from anywhere and anytime with the help and mobile device and internet technology (Duman et al., 2015). That means disseminating quality learning materials through mobile devices. Most of the learning management system delivers the fixed materials to all the learners. But the success of any learning system is not only delivering educational contents to the learners but also understand the learning nature of the learner and knowledge level and needs. This has led to several research initiatives worldwide that investigate the potentials of the educational paradigm shift from the traditional teaching approaches to adaptive and personalized learning (Lo

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et al., 2012). Personalized learning considers the learning methods and contents are tailored towards the learner's needs, skills and interest and adapt the course content (customizing learning material/contents). Personalized learning will help both learners and instructors in such a way that learners can get customized learning content/material based his/her learning pace, style and need. This will increase the learning interest, maximize the learner's satisfaction and achieve the learning outcomes. On the other hand, instructor will also understand the need of the each and every learner, learning pace, style, preferences etc. this will help the instructor to customize the learning material and design which is more suitable and attract large learner community. This paper presents the personalized mobile learning recommendation system which considers learning style of the learner in order to select the proper content type and grade achieved by the learner in the courses are considered for course recommendation by using naïve bayes theorem.

Rest of the paper is organized as follows. Section 2 presents the overview of existing personalized mobile learning and recommendation system. Section 3 presents the learner style and content design. In Section 4, describes the proposed system and data analysis and finally we conclude the paper in section 5.

PERSONALIZED MOBILE LEARNING AND RECOMMENDER SYSTEM

Rapid proliferation of mobile and internet technology has potentially promoted the diverse learning approaches. Personalization in learning, boosts the interest in learning process which helps the learner to achieve their learning objective/outcomes (Muna, 2019). In this section, presents the overview of existing personalized mobile learning and recommender system.

Benlamri and Zhang (Benlamri & Zhang, 2014) presented context aware recommender system for mobile learning which has proactive context awareness mechanism that can sense both system centric and learner centric context and adopts the accessed services accordingly at run time. Personalization is achieved based on the learner's background knowledge, preferences, previous learning activity, covered concepts, adapted learning path and consumed learning resources. Then the system will construct new learning sequence for learner that consist of optimized system-centric learning resources to fulfill the current learner's activity and goal.

Inssaf El Guabassi et.al (El Guabassi et al., 2018) presented the personalized course content adaptation system which considers learner profile as the base for content adaption learner. The learner profile consists of four attributes such as Learning Style(Visual, Verbal, Global, Sequential, Reflexive, Intuitive, Active, Sensing), Cognitive Style (Text, Audio, Video), Cognitive State (Beginner, Intermediate, Expert) and Device context(Device, Activity, Environment) . Based on the learner profile, course content will be adapted.

Brita Curum et.al (Curum, Chellapermal, & Khedo, 2017) proposed mobile learning system in which personalization is achieved by adopting the course based on learner age (11-17 -Junior, 18-45 Adult and 46-65 Senior) Junior and Senior learners are presented with courses which carries basic explanations while adults are presented with explicitly detailed contents. Difficulty of the assessment questions depends on the quiz level (beginner, intermediate, advanced) and the user age group.

Tortorella and Graf (Tortorella & Graf, 2012) proposed an approach for providing personalized course content in mobile settings, considering learner's learning style and context. In this system, course is divided into sections and each section into serious of lectures. These lectures are further divided into smaller blocks. The material of each of these blocks is recorded in four different modes (video, audio, text and powerpoint). The course material is stored electrically in various appropriate file formats on the server and presented via mobile device. These blocks must be numerous and short enough to allow for a dynamic personalization by changing the delivery mode as required.

Brita Curum et.al (Curum, Gumbheer, Khedo et al, 2017) presented a context-aware mobile learning application "Mobiware" which uses contextual data for content adaptation. Contextual data includes physical context adaptation (Location, Time, Environmental Condition, Network Capabilities) and user context adaptations (Preferences, Prior Knowledge, Learning Style or Comprehension Level (Slow, Moderate, Speed Learner), Attentiveness (how much time the learner is ready to allocate), Learning Intention (Learner interaction with the system).

Brita Curum and Kavi Kumar Khedo (Curum & Khedo, 2015) pointed out the cognitive load to the users in mobile learning platform is the central for instruction design for course material and course material adaptation for personalized learning.

Shivam Saryar et.al (Saryar et al., 2019) proposed a mobile learning application which implements Felder Silverman Learning Style (FSLSM) and recommendation component model. Learning style is used to identify the learning nature of the user. Based on learning style as well as user activities, course material recommendation are provided to the user by the recommendation system.

Most of the existing system includes the learner profile (which considers the learning style is the highest priority), context and content delivery for personalized mobile learning. Some of the papers discussed about learning recommendations specially to understand and refine the learners interest/learning style, based on learner's activity / interaction. It is not enough to simply understand the learning style or interest alone for personalized learning. It should also suggest systematic way of choosing best courses for learner to increase the learners score in quiz/test.

LEARNING STYLE

Learners are having different ways to acquiring knowledge. Design of learning material and delivery should be based on the learners learning style. Mismatches between learners learning style and teaching/learning object delivery leads to boring and inattentive in course, poor performance in the tests/quizzes, gets discouraged about the courses, the curriculum and finally drop-out from the course (Felder, 1988). Learning style focuses on individual learning capabilities, learning path, preferred learning content and performance (Cassidy & Styles, 2004). It is a combination of cognitive, effective and psychological characteristics that indicate the learner's way of processing, grasping, understanding and perception capabilities towards the course contents. It also helps to find the learner's learning preferences and shows the positive results in the form of increasing learning satisfaction, improving grades, decreasing time required to acquire new knowledge (Tortorella & Graf, 2017). Hence understanding the learners' needs and identifying their learning style, preferences are crucial to design a learning material as shown in Figure 1.

There are two main methods to find the learning styles (Kolekar et al., 2014) such as 1. Literature based Method and 2. Questionnaire based Method. Literature based method helps to find the dynamic nature of the learners learning style by monitoring learner's activities such as time spent on materials, time spent in tests, type of learning objects, skipping of learning objects, count of various learning

Figure 1. Relationship between learner's learning style and learning material design

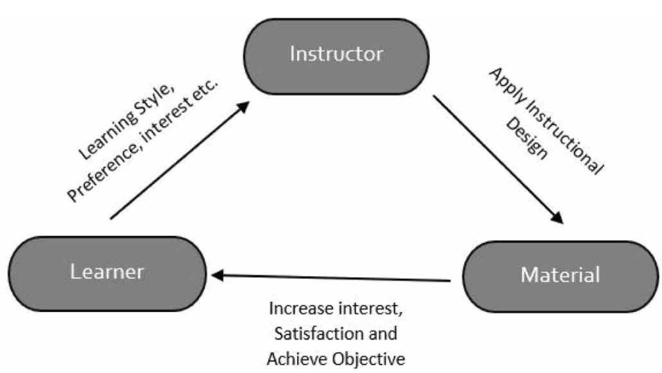


Table 1. Felder Silverman Learning Style Model

Learning Style	Description
Active (ACT)	Prefers to try things out, working with others in groups
Reflective (REF)	Prefers thinking things quietly and working alone or work with one other person whom they know well.
Sensing (SNS)	Prefers to learn facts, like to solve problems by well established methods and dislike complications and surprises. Sensors tend to be patient with details and good at memorizing facts, doing hands-on work(Lab), more practical and careful and don't like courses that have no apparent connection to the real world.
Intuitive (INT)	Prefers discovering possibilities and relationships, likes innovation, better at grasping new concepts and comfortable with abstraction and mathematical formulations. Intuitors tends to work faster than sensors and dislike repetition and plug-and-chug courses.
Visual (VIS)	Prefers visual representations such as pictures, diagrams, flow charts, timelines, films, demonstrations etc. Remembers best what they have seen.
Verbal (VER)	Prefers written and spoken explanations.
Sequential (SEQ)	Prefers to gain understanding in linear steps, with each step following logically from previous one and follows logical stepwise paths in finding solutions.
Global (GLO)	Prefers to learn in large jumps, absorbing materials almost randomly without seeing connection and suddenly getting it. Solve complex problems quickly or put things together in novel ways one they have grasped the big picture but they may have difficulty explaining how they did it.

Figure 2. FSLSM-ILS Sample Score

ACT/REF			SNS/INT			VIS/VER			SEQ/GLO		
Q	**a**	**b**	**Q**	**a**	**b**	**Q**	**a**	**b**	**Q**	**a**	**b**
1	0	1	2	1	0	3	0	1	4	1	0
5	0	1	6	1	1	7	1	0	8	0	1
9	1	0	10	1	0	11	1	0	12	0	1
13	1	0	14	1	0	15	1	0	16	1	0
17	0	1	18	0	0	19	1	0	20	0	1
21	1	0	22	0	1	23	1	0	24	1	0
25	1	0	26	0	1	27	1	0	28	0	1
29	0	1	30	1	0	31	1	0	32	0	1
33	0	1	34	1	0	35	1	0	36	0	1
37	1	0	38	0	1	39	1	0	40	0	1
41	1	0	42	1	0	43	1	0	44	0	1

Q	**a**	**b**	**Q**	**a**	**b**	**Q**	**a**	**b**	**Q**	**a**	**b**
	6	**5**		**7**	**4**		**10**	**1**		**3**	**8**
	1a			**3a**			**9a**			**5b**	

Table 2. Mapping the learning style into preferred Learning Object (LO) (Saryar et al., 2019) (Tortorella & Graf, 2017)

No.	Learning Object	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
1	Text								
2	Audio								
3	Video								
4	Exercise/Problems								

objects, performance in the tests and navigation (Premlatha et al., 2016). Questionnaire based method uses the questions to find the learner's learning style. There are several questionnaire-based methods are available in the literature some of them are Felder Silverman Learning Style Model [FSLSM] (Felder, 1988), Myers-Briggs type indicator(Briggs, 1962), Honey & Mumford(1982), Kolb(1984), and Pask (1976). But FSLSM combines several major learning style models and most appropriate for hypermedia courseware (Carver, 1999). FSLSM characterizes each learner according to four dimensions: active/reflective, sensing/intuitive, visual/verbal and sequential/global as shown in table 1. FSLSM-Index of Learning Style questionnaire is comprised of 44 questions and the result of the ILS questionnaire are four values for each dimension.

FSLSM- ILS sample scoring sheet is given in Figure 2. Value 1 is placed if answered, 0 otherwise.

Table 2 presents the mapping of learning style into preferred learning object.

In order to find the most preferred content format to the learner, calculate the score for each learning object for the learner using the formulas (1) (2) (3) (4) presented below.

From the sample score of a learner (TextScore is 13, AudioScore is 16, VideoScore is 26 and Exercise/ProblemScore is 20), the system will rank the LO based on the score and it will be stored in learner profile. System will recommend the LO by choosing the top two or best two LO format in LO ranking. Remaining LO are optional to the learner.

Algorithm 1. Computer Learning Preference

```
Initialize two integer array and local integer variables
a[44]=0, b[44]=0
// Variable for 8 learning styles
ACT=0,REF=0,SNS=0,INT=0,VIS=0,VER=0,SEQ=0,GLO=0
//Variable for different LO score
TextScore=0, AudioScore=0, VideoScore=0, Exercise_problem_Score=0
// Variable for two high LO scores
High1=0, High2=0;
//Open and read ILS.txt line by line
sc <= ILS.txt
i=0
while (sc has line) do
    data <=line
    while (data has more token) do
        if first then a[i]=token
        else    b[i]=token
    end while
end while
close sc
// Compute score for each learning style
for c=1 to 11 do
```

```
    if a[c]==1 then ACT =ACT+1
    else if b[c]==1 then REF =REF+1
    if a[c+1]==1 then SNS =SNS+1
    else if b[c+1]==1 then INT =INT+1
    if a[c+2]==1 then VIS =VIS+1
    else if b[c+2]==1 then VER =VER+1
    if a[c+3]==1 then SEQ =SEQ+1
    else if b[c+3]==1 then GLO =GLO+1
end for
// Compute score for learning preference
TextScore=REF+INT+VER+SEQ
AudioScore=REF+SNS+VER+SEQ
VideoScore=SNS+INT+VIS+GLO
Exercise_problem_Score =ACT+SNS+INT+SEQ
arr[] = [TextScore,AudioScore, VideoScore,ExeciseScore]
sort(arr)
high1=arr[3]
high2=arr[2]
if TextScore ==high1  or  TextScore ==high2 then LO-Type Text
if AudioScore ==high1 or AudioScore ==high2 then LO-Type Audio if
VideoScore ==high1 or VideoScore ==high2 then LO-Type Video
if Exercise_problem_Score ==high1 or Exercise_problem_Score
==high2 then LO-Type Exercise and Problems
```

COURSE CONTENT

Success of mobile learning is relying on quality of the course content. The content may include descriptions, definitions, concepts, exercises, problems, explanations, principles and practices. Based on curriculum, level and objective, the course contents are designed by the instructors. In general learning content developments are either macro or micro style. Macro learning style learner should spend more time (hours) to study the learning material in order to attain the required skills/knowledge. Learner requires the assistance from the Instructor in the classroom and the course exercises are evaluated by Instructor. But in micro learning style (Bruck et al., 2012) the contents are organized like small chunks or nuggets. Most essential contents extracted and are included in the micro learning and it is the best suited for the mobile learning. Learners may spend (2 to 10 mins or not exceed 20 mins) every chapter or topic to learn. Assessment can be done automatically because most of assessment can have objective type questions. It requires very minimal intervention from instructor.

In proposed system, the learning contents developed based on Micro learning style . Initially the courses are grouped based on the specialization for example courses in computer science are grouped into specialization such as Software Engineering (SE (Theory & Programming)), Database(DB), Networking(NT), Information Security(IS) and then the contents are divided into small chunks such as Chapters and Sections. In each section, contents are designed in different LO format. Every course must have unique code and having level (Basic level, Intermediate Level and Advanced Level). Every course is also having assessment in the form quiz and every learner of the course must take the quiz in order to get the grade in the course.

LEARNER PROFILE

Learner's profile is the important source of personalization in mobile learning. There are several parameters to be considered for personalized learning such learner's situation, intention, nature of learning, preferences, state, age, navigation stream, score etc. The proposed system considers the most important parameters such as personal data, preferences and grade.

- **Learner's Personal data:** Contains the learner's name, id, date of birth, contact number, user id, password etc.
- **Learner's Preferences:** Learning styles represent a combination of cognitive, effective and psychological characteristics that indicate the learner's way of processing, grasping, understanding and perception capabilities towards the course contents. It also helps to find the learner's learning preferences and shows the positive results in the form of increasing learning satisfaction, improving grades, decreasing time required to acquire new knowledge (Tortorella & Graf, 2017). In our proposed system, learner's preferred learning objects are identified the ILS test and subsequent learner's LO visit count. Every visit of learning object is counted and updated in the learner's profile in order to compute the learner's learning preference at the time of the learner completes course.
- **Course Grade:** Learners progress and behaviors are monitored, and statistical feedback is analyzed to improve course effectiveness. So, every course grade of the learner is saved in the learner profile for course recommendations. Course grades are listed in the Table 3.

Table 3. Course Grades

Percentage of Marks	Grades
85 – 100	A
75-84	B
60-74	C
Less than 60	D

PREDICTION AND RECOMMENDATION

Naive Bayes is a probabilistic machine learning algorithm that can be used in a wide variety of classification tasks. Typical applications include filtering spam, classifying documents, sentiment prediction etc. Our proposed course prediction and recommendation system based on Naive Bayes algorithm.

$$P\left(A|B\right) = P\left(B|A\right).\frac{P\left(A\right)}{P\left(B\right)} \tag{5}$$

In our problem of course recommendation,

Consider G is grade such as A, B, C, D
Consider L is level such as Basic, Intermediate, Advanced
Consider S is specialization such as SE, DB, INT, IS

$$G_n = \left\{G_1, G_2, G_3, \ldots G_n\right\}$$

$$L_n = \left\{L_1, L_2, L_3, \ldots L_n\right\}$$

$$S_n = \left\{ S_1, S_2, S_3, \ldots S_n \right\}$$

$$Let\, X = G_n, L_n, S_n$$

$$P(G_n \mid X) = P\left(G_n\right) * P(L_n \mid G_n) * P(S_n \mid G_n) \tag{6}$$

Using Bayes theorem, we can find the probability of A happening, given that B has occurred. Here, B is the evidence and A is the hypothesis. The assumption made here is that the predictors/ features are independent. Figure 3 shows the learner transactions.

Figure 3. Learner's Transaction

TR	LE-ID	COURSE_CODE	COURSE_TYPE	COURSE_LEVEL	GRADE
1	1020101	SE101	SE	Basic	B
2	1020101	SE102	SE	Basic	A
3	1020101	SE103	SE	Basic	C
4	1020101	DB101	DB	Basic	A
5	1020101	NT101	NET	Basic	B
6	1020101	NT201	NET	Int	B
7	1020101	DB202	DB	Int	C
8	1020101	DB201	DB	Int	C
9	1020101	IS301	IS	Adv	C
10	1020101	IS103	IS	Basic	D

Figure 4. Probability to achieve the grade

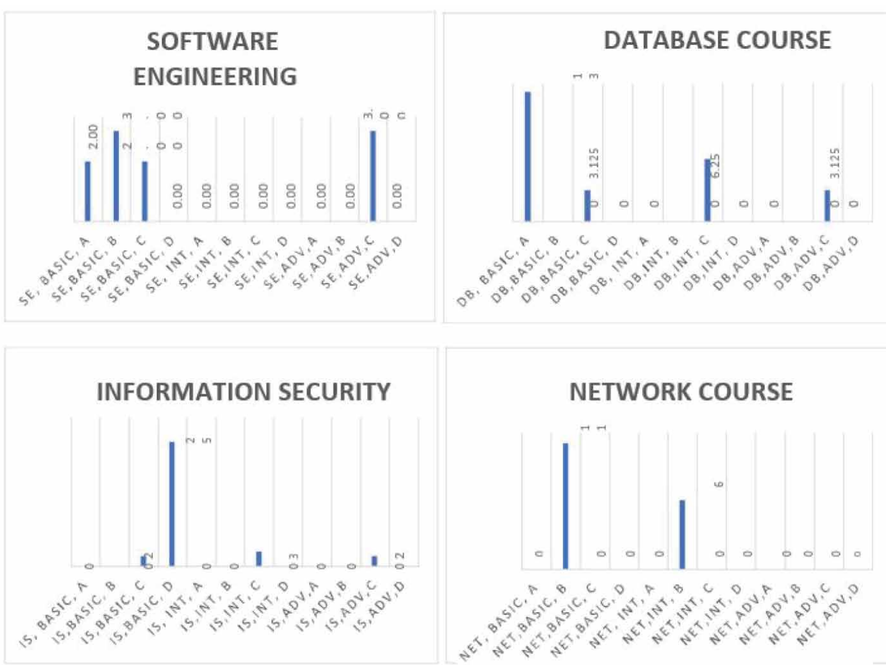


Figure 4 presents the probabilities for the learner to achieve the grades in different specialization.

Course Recommendation are based on the following formula. High grades are calculated by adding probability percentage of A and B grade and then top percentage's specialization in the level is/are recommended. If there is 0 grade in any level and in all four specializations, low grades will be calculated by adding probability percentage of C and D grade for that level only and then top percentage's specialization in the level is/are recommended.

$$High\,Grade = \{_{L_1}^{L_3} \{_{S_1}^{S_4} \, Percentage\,of\,A + Percentage\,of\,B \tag{7}$$

$$Low\,Grade = \{_{L_1}^{L_3} \{_{S_1}^{S_4} \, Percentage\,of\,C + Percentage\,of\,D \tag{8}$$

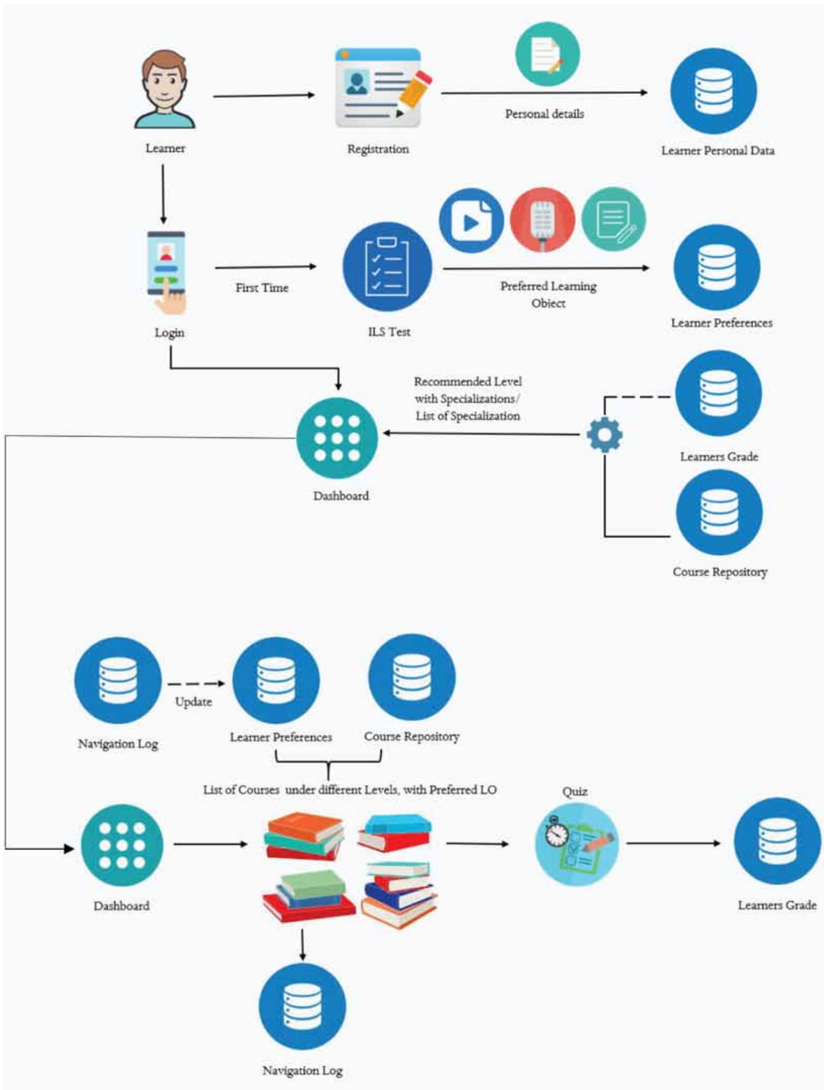
SYSTEM DESIGN

The proposed system consists of several modules:

1. **Registration, Login and Logout:** Every Learner must register in the system in order to use it. Once the learner is registered, the learner's details (name, id, age, password, mail id etc) will be stored in the learner profile and learner can login using his/her id and password.
2. **ILS Test and Quiz:** Every registered learner must take this ILS test when he/she login first time after registration. ILS testis used to find the learner's preferred learning object. Once after the ILS test, learner's preferences will be stored in learner profile. Quiz is based on course. Once the learner completes the course, he/she must take the quiz in order to get the grade in the course. Course grades are used for course recommendation.
3. **Dashboard:** Dashboard is the main user interface for navigation. All the specializations are listed in the dashboard for learner to select. Learners can select any specialization as they prefer. Dashboard also display the recommendation which includes specialization with level.
4. **Course:** Each specialization is having list of courses under different level. Learner can choose any level and courses. Each course contents are presented in three different formats called learning object (LO). Based on the user preference in ILS test, learning objects are presented to the learners.
5. **Navigation Log:** When the user interacting with LO of any course in any level is stored in navigation log.

The learner preferences are updated based on the learner's navigation log. Whenever learner completes the Quiz of any course, the learner's preferences will be updated.

Figure 5. System Design



CONCLUSION

Personalization is the key factor for the success of any mobile application and its services. Mobile learning applications is not an exceptional too. Mobile learning helps the learner to learn anything, at any time, from anywhere through support of internet. This will help the learners to acquire the required knowledge for anywhere. People are addict of using m-learning application from school children to adult of any age. Providing unique and personalized service promotes any m-learning application into next level of learning culture. This paper presents the existing personalized m-learning frameworks and its features. It also presents the different parameters for personalization and recommendation. The proposed system provides the adaptable mobile learning application with personalized learning and course recommendation feature. The course recommendations are based on naïve bayse theorem and explained with sample data. In future, this system will be more personalized with learner's navigation log data.

Conflicts of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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