Journal of Theoretical and Applied Information Technology
30th November 2021. Vol.99. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ADAPTIVE E-LEARNING RECOMMENDATION MODEL BASED ON THE KNOWLEDGE LEVEL AND LEARNING STYLE

ALBER S. AZIZ[1], REDA A. El-KHORIBI[2], SHEREEN A. TAIE[3]

[1]Department of Computer Science, Faculty of Computers and Information, October 6 University, Giza, Egypt
[2]Department of Computer Science, Faculty of Computers and Information, Cairo University, Cairo, Egypt
[1,3]Department of Computer Science, Faculty of Computers and Information, Fayoum University, Fayoum, Egypt

E-mail, [1]albershawky.csis@o6u.edu.eg, [1]as2407@fayoum.edu.eg, [2]ralkhoribi@staff.cu.edu.eg, [3]sat00@fayoum.edu.eg

ABSTRACT

E-learning systems facilitate the process of education and interaction between teachers and learners during minimizing a lot of temporal or spatial restrictions. Recently, many learners prefer to use electronic devices to achieve everyday jobs. The process of using the learner style, learning goals, and learner characteristics, and electronic devices and systems are called Adaptive e-learning. The importance of Adaptive E-learning Systems (AES) is to help the teachers to choose and recommend some materials to the learner and to increase the knowledge level. This paper develops a new adaptive e-learning recommender model using learning style and Knowledge Level Modeling (AERM-KLLS). The proposed model adapted automatically to the requirements, interests, and levels of knowledge of the learners by analyzing learner style using a fast questionnaire, representing the knowledge level and all the course questions in the learner model as a knowledge overlay model, which helps the proposed model to recommend objects from the points that have the least scores at the pre-test. The analysis of AERM-KLLS performance measured by making two tests and comparing the two test performance; the performance of using the AERM-KLLS algorithm used in the second test for 321 participated learners increases the overall performance for the students with an accuracy of 90.97%. The proposed model provided to the learners for an English course in the Faculty of Computer Science, October 6University, to make the best use of the E-learning advantage and increasing the performance, in COVID 19 restrictions.

Keywords: *Learning Style, Knowledge level, Questionnaire, Adaptive E-Learning*

1. INTRODUCTION

The uprising of numerical knowledge has directed to establish a modern educational space with a new chance to teach people. The digital technology specificity is transferred by teachers or discovered by learners by data and announcement technologies, and the program facilitates conversation contact, in which learners can correct their errors as well as enhance their learning capabilities [1]. The expression "adaptive e-learning educational system" adjusts the learning knowledge for each student. Each individual has his own characteristics. They show different actions to form convinced set features that led to good grouping. Therefore, these groups help teachers to afford necessary educational materials. Most of these systems (adaptive e-learning systems) don't treat learners individually. They don't take into account the learning style (LS) factors and offer the same learning materials to all learners as ‘‘one size fits all’’. Personalization in e-learning systems is developed in a way to provide learning in the preferred style of learning to reduce learning gaps and improve learning [2]. Outputs depend on input variables; therefore they also change [3].

The neural network concept, ambiguous logics, and ambiguous cognitive maps duplicate the functions of the human brain. This intelligence system is introduced by making appropriate expectations about LS preferences, knowledge levels, behavioral aspects, and the learner's psychometric analysis [4]. These methods are very useful in determining what the learner prefers and what the teacher must provide dynamically. Fuzzy values [5], the studies relevant to education and analysis of human behavior are understood to be in the field of soft computing. The recent study in e-learning depends on the recommendation methods that are likely to increase the performance of the entire learning process. Therefore, it is essential to develop a new recommendation system to offer better facilities to learners.

The well-known recommendation systems have some disadvantages like the greater variances in the measures of presentation and requiring a complex computational, which leads to less accuracy of recommendation; therefore, it's essential to advance modern recommendation methods to balance these challenges to determine answers to different e-learning topics. To overcome these problems, automatic ideas [4], [5] are presented to detect the LS of learners according to their performance while using the e-learning system [6]. This way has some advantages above the normal methods. First, it gathers information through the interaction of learners with the system [7]. Furthermore, LSs are automatically founded in a dynamic way and change according to the interaction of learners with the system [8], [9].

This research offers a new personalized e-learning recommender model using LS and KL that implementing some strategies required offering better recommendations compared to the current techniques. The suggested model was performed on the dataset with 321 learners. The experimental results let us determine that the learners from the simulation set could study a course with minimum computational time compared to the other no-recommender set.

The suggested model was also found to intelligently recommend learning resources based on LK and style. The main strategy used in this research is to identify and keep knowledge level when the learners take a number of test items related to each learning main point (LMP). This strategy can be performed by mapping the questions and the learning materials to each LMP. This model is a multi-level model that calculates and stores the marks; the model calculates the value of each LMP knowledge level from the learner's answer. After that, calculates the course knowledge level. In Egypt, at the beginning of March 2020, COVID19 (corona virus) stops studying in traditional groups until the students will return; Universities have to start using online classrooms. A real system was designed to apply our model for one course (English course) in 2021.

The contribution of this paper is proposing new personal e-learning recommending model (AERM-KLLS) to qualify the learner to learn and understand professionally. Furthermore, this paper is suggesting a new model that recommends materials based on the LS and knowledge level that identify and store the knowledge level. The suggested model's overall accuracy is 90.97%.

This paper is organized as follows; Section 2 discusses the background and some important algorithms. Section 3 discusses the associated works about several procedures are used to define and classify LSs through different LS models. Section 4 shows the suggested model. Section 5 discusses and presents the Experiment and results. Finally, Section 6 presents the conclusion.

2. PRIM LINES

The goal of adaptive e-learning is to convey the right material objects, to the right learner, in the most suitable way. To build an adaptive e-learning recommending system, some important concepts such as Adaptive E-Learning, Adaptive E-Learning Systems, Categories and benefits of adaptation in e-Learning environments and some learner characteristics such as LS and LK that will be used in the proposed method were explained in this section.

2.1 Adaptive E-Learning

Adaptive e-learning offers a way of adaptively in which learners have options to determine the time, site, favorites, and demand at their own will to get the preferred learning materials at the process of learning. Then, the e-learning system begins to develop a suitable e-learning system where learners experience modified and personalized learning

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

processes. It deduces the learners' characteristics to identify the learner's preference to create a personalized learning route and modified learning materials for the learners. After that, it is important to make a suitable recommender system [6].

2.2 Adaptive E-Learning Systems

It is a more advanced and improvised e-learning system in which LS and other behavioral features like previous knowledge, emotions, activities, etc., are auto-detected and taken into account in the provision of learning materials according to the choices made by the informed, uninformed or automatic learners by the system on the basis of auto-detected log files [4]. Adaptability increases learning speed, learning experience, and learning outcomes [5]. An adaptive e-learning system is a process of merging and collecting some of the techniques which lead to adapt the process of e-learning.

2.3 Goals and Benefits of adaptive e-Learning

The aim of adaptive e-learning is to convey the right material objects, to the right learner, in the most suitable way, to make the interaction with system simple, friendlier, and efficient [10], another important goal of adaptively is to improve the system environments. The system can present to the learner useful links or paths to route through course materials. According to the learner's differences in LS and knowledge, the system has the ability to provide modified access to the objects. The decisions of presenting the objects are depends on the user's profile enables the system to personalize the choices to the learners [11]. The aims of AES are presenting the right learning objects to the right learner, at a suitable time, providing some links and paths, which can matches learning styles and adapt strategies, finally observing the learning processes, producing reports, and providing guidance to the suitable objects more efficiently.

2.4 Categories of adaptation in e-Learning environments

There are many classifications of adaptation in e-Learning environments [12], which have been defined for facilitating and supporting the introduction of adaptive techniques and depending on the main learner characteristics.

2.4.1 Adaptive Interaction

This category talks about the changes that happen at the system's interface and are modified to ease or support the user's dealings with the system, without changing in any way the objects themselves. This change includes the use of different graphics or color patterns, suitable font size, etc., to suit user favorites, requests, or capabilities; the restructure or rearranging of interactive process at the syntactic level [2].

2.4.2 Adaptive Course Delivery

This category is the most used and consists of a set of adaptation techniques that adapts a course to each learner, to improve the compatibility of course contents and user requirements, so that saves the learner time and effort. Key factors of the adaptation techniques include: the system simulates a human teacher, who can discover learner characteristics, goals, etc., improve course self-assessment by learners, etc. The most adaptations examples in this category are adaptive navigation support; dynamic course restructuring; and, adaptive selection course material [2].

2.4.3 Content Discovery and Assembly

This category talks about the use of adaptive techniques in the detection and rearranging of learning material. The adaptive section of this method lies with the use of adaptation-focused on models and data about users typically resulting from observing. In this category, we would like to make an obvious distinction between the viewpoint of any learner hoping to locate appropriate material within a (possibly forced) corpus, and the perspective of the author or "aggregator" who carry out the task of designing a course from obtainable materials and aiming specific addressees[12].

2.4.4 Adaptive Collaboration

Adaptive Collaboration aims to gain adaptive support in learning operations that consists of collaboration, social interactions, and communication among many learners. This factor is important to be seen as what modern learning techniques used to facilitate the interaction, collaboration, and communication process [12].

2.5 Learning Styles

LS is a distinguishing feature of the student and an educational strategy. As the important learner characteristic, LS refers to how a learner learns and prefers to learn [13]. As an educational strategy, it provides information about context, cognition, and objects of learning aspects. The LS can be described as the way that a learner uses to study information and easy to understand.

2.5.1 The Felder and Silverman Learning Style Model (FSLSM)

The FSLSM gives good results with educational systems by explaining four dimensions (processing, perception, input, and understanding) of the learner LS as shown in figure 1. Each dimension divided into two categories; the learner behavior belongs to one category from each dimension [13].

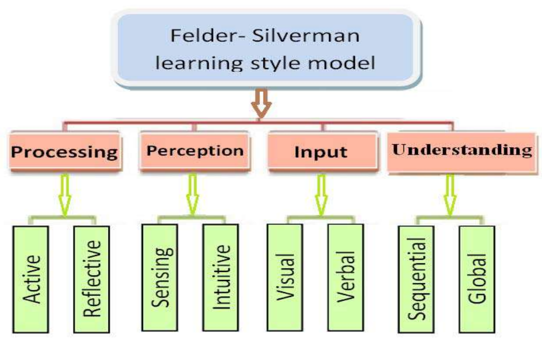

Figure 1: Felder-Silverman Learning Style Model[14]

2.5.2 Algorithm to Initial LS

A lot of algorithms used to predict LS, the questionnaire of Ulearn algorithm [14], personalized learner's profile based on dynamic learning style questionnaire does not waste time. This algorithm computes dynamically the initial LS even if the leaner did not answer all the questions at this dimension; with the Ulearn questionnaire, answering the questionnaire is saving time and not a boring process.

It demands from the learner to take 11 questions at each dimension, the learner select ("a" or "b").from the answers this algorithm can discover the learner category.

The algorithm of the Ulearn questionnaire is:

```
Start

For each dimension from 1 to 4 do
Select_A[dimension] = 0;  //initialize
Select_B[dimension] = 0;
Question = 1;
While    (Select_A[dimension]    <7    and
Select_B[dimension] <7 and Question <=11) do
        Read the question answer;
        If (learner Select  is "a") then
          Select_A[dimension] =
          Select_A[dimension] +1;
        Else
          Select_B[dimension] =
          Select_B[dimension] +1;
        End if
        Question= Question+1;    ///next question
End While
End for
End
```

The description of this algorithm by the input and the output of the algorithm is as follows:

Input data to the Algorithm: the learner 11 answers at each dimension.

The process: at each dimension, the algorithm counts the total number of "a" and the total number of "b", the maximum counted number indicates the category. For example, if the number of "b" greater than "a", the learner is reflective otherwise is active.

The output: 4 learner categories.

2.6 Knowledge

User knowledge can maximize (learn) or decrease (forget) while the learner interacts with the system at the same session. An adaptive system that is based on user knowledge must detect the changes in the level of LK and store the changes at the user model as a result.

The scalar model is considered the simplest form of an LK, which calculates the level of LK at one value on a quantitative number, for example from 0 to 5, or qualitative word (for example, beginner, good, average, expert, none). The scalar knowledge models concentrate on user knowledge and are typically generated by the learner self-assessment. Although simple, standard models can be used effectively to provide simple adaptation for e-learning systems. These systems divide the learners into three or four categories based on their level of knowledge of the topic.

An example of adaptive presentation depending on a scalar model is the ALS-KL [15] system. It is an adaptive learning system that can customize subjects due to the level of proficiency of learners. An initial test is taken to measure the proficiency knowledge level of learners. The learners are divided into primary, middle, and advanced.

The scalar model is not sufficient for any advanced adaptation technique that should consider some aspect of user knowledge. Therefore, adaptive e-learning systems that concentrates on advancing user knowledge uses different types of structural models. Those models assume that the domain knowledge body can be divided into a set of independent parts, to represent the LK of different parts independently.

The overlay model is the most famous model of the structural knowledge model [16]. The target of this model is to declare and represent the personal LK by a subset of the domain model, which indicates the knowledge level of the subject. The overlay model uses a Boolean value, 1 or 0, for each part, to realize if the user knows or does not know this part. So, user knowledge at every moment of time is represented as an accurate subset or "overlay" of expert knowledge.

3. RELATED WORKS

Several current e-learning systems were founded based on the ways of learning, types of information, learner features, and other specific structures of operational techniques. A custom recommended model was developed using learning and technology assembly to analyze educational tracks [17]. Customized object-based Target learning objects have been analyzed with different learning methods using a clustering algorithm [18], learning patterns and knowledge levels of education were used as content filtering [1]. Selecting learning styles automatically with different LS models [19] [20].

Various techniques use the collected data gathered from the learners' interactions during the learning process. In this style, the detection is done by means of a simulated intelligent classification process. The learners' transactions considered as input to the system and the learners' LS as output. Logically, this approach uses real data to discover the LS; it can be very accurate by providing expressive data for the purpose of classification. The learners' behaviors need to be extracted. So, web mining techniques are used to provide this classification [21]. Furthermore, in the field of programmed recognition of learning styles, different features of learner behavior must be considered when designing the detection method. In addition, these features are needed in tentative tests to obtain the accuracy and to increase it.

In [22] a new method is used to recognize the LS of each learner Using FSLSM. The learner's style has been taken out from Moodle log to classify the LS automatically, decision tree algorithms were used for classification. The performance of this method was detected at the end of the course by comparing LS based on the quiz grades. But, this method used for a single online course, and is investigated only on 35 learners.

The fuzzy logic was also used to detect the learner's learning style automatically [23][24]have used an ambiguous classification tree by building an ambiguous prognostic model. In this model, the writers use autonomous variables which are taken from natural language discussion. Through this piece of work S. Kolekar [25], the online mining technique helps capture learning behavior. Then, it is changed to XML format based on the evaluation of the sequences of content. These sequences are assigned to the FSLSM eight classes by using the FCM algorithm. Then, (GSBPNN) algorithm can be used to predict LS for the novel learner. With this algorithm, an adjustment to NN is made by calculating the weights of the gravitational search algorithm. The total number of 108 learners studied the online course; the resolution of the classification algorithm performance is 95.93% after 200 iterations. The higher the repetition numbers, the more accurate the results are. However, the algorithm takes longer to execute. However, only one course has been created for the learners to follow.

D. HASSOUNA [26] recommended a platform was practiced on a 200 learner college from Canadian International College to maximize the operation of advanced education and can be trained online or materially at the university. This work

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

used the VARK survey [27], which offers students 16 multiple choices questions, the learner will choose the best answer based on his preferences. The results were elevated by a 50% success percentage with 200 learners.

Authors in [28] offered a personalized LSs prediction based on the Moodle LMS and used the data mining techniques to analyze the log file and the learner transactions. A performance computation and comparison was declared in this study of several data mining techniques. However, this study was applied for one online course. Examining the most common learner characteristics shared in previous efforts reveals that most AES consider up to three learner uniqueness in a lot of models typically, KL, preference, and LS [29].

The most common characteristics of the learners are the learner's level of knowledge and LS or preferences.LK is used in many models of learning as the main factor followed by LS in promoting learning in an instructional context [30].A lot of factors, models should be considered to notify the adaptation model [10]. The main task is to identify which adaptive techniques are most effective in AES to classify displaying data, navigation, and adaptive content. Another important challenge is how AES can provide adaptation and when particularly for the models that integrate LS and KL.

4. THE METHODOLOGY

The objective of the AERM-KLLS model is to increase the LK of the learner that affects directly the overall performance of the learner by predicting the LS and direct the learner to the course materials that support his LS. Therefore, the model presents to the learner the needed objects according to LS. As shown in figure 2. The learner starts to sign up to create an account and fills in personal data and answers the questionnaire to discover the LS. Then, the model recommends the mapped learning objects to each LS cluster.

Finally, the model will recommend subjects based on the new LS and level of knowledge followed by a post-test. The proposed model algorithm illustrated in the following steps:

AERM-KLLS Algorithm

1-for each unit at English course:

a. Divide the unit into main points.
b. Match each main point with the learning objects.
c. Match each main point with the questions at the test bank.

2- End for

3-The learner starts to sign up:

a. Create an account and fill in personal data.
b. Answer the questions of the questionnaire.
c. Discover the LS using Ulearn Questionnaire.
d. Clustering each LS to one of 16 clusters.
e. Mapping the learning objects to the learner.

4-The learner study before the first test:

a. The system recommends the mapped learning objects to each LS cluster.
b. The learner opens the recommended objects and starts to learn.
c. The system uses the learner log file to store all activities.
d. find the sequences weights using Learner activities and current LS

5- The learner solves the pre-test.

6- Update the LK based on pre-test results. and update LS based on AFCM

7- Repeat step 4(the model will recommend materials based on the LS and knowledge level).

8- The learner solves the post-test.

9- Update the LK based on post-test results.

The proposed model comprised of three phases.

Phase 1, Initialization of the learner profile, domain model, and the LS.
Phase 2, recommending the mapped learning objects to each LS cluster.
Phase 3, recommending the learning objects to each LS cluster based on knowledge level.

The three phases will be illustrated in detail in the following sections:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.1 Initialization of the learner profile, domain model, and the LS

This phase starts to collect personal data about the learner such as (Name, Id, Login Password, Birth date, GPA, faculty-Email, Phone Number, and Course information) to initialize and create the Learner profile. Also, creates the domain model and discover The LS using the Ulearn questionnaire. The model can describe phase one in the following 2 points:

4.1.1 Create Domain Model

The aim of the domain model is to store and represent the learning material objects in somehow that it easier to recommend the objects to the learner and to adapt the system, as shown in figure 3. This model is represented in a hierarchical way consists of three levels to represent the course domain model.

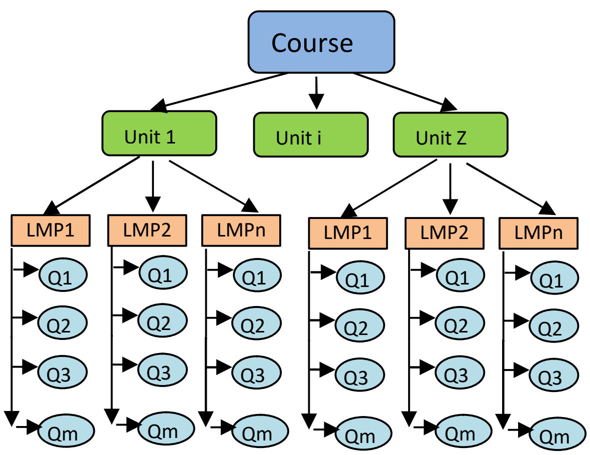

Figure 3: Example of a domain model structure (LMP = learning main point or concept).

At level 1, the selected course consists of Z units, each unit deals with one part of the whole course.

Level 2, divides each unit into N of learning main points (LMPs) which are not the same for all units. The LMPs are selected and classified depending on the teaching style, for example at English course unit 4 divided into 3 LMPs (conditional sentences type 1, conditional sentences type 2, and conditional sentences type 3).

Level 3, Each LMP contains a set of learning objects, and M questions focus on the selected LMP. This design is very important to make mapping between any test questions and All LMPs.

4.1.2 Discover the initial LS

At this step, the learner fills the FSLSM questionnaire [14] in order to discover the LS and match it to one cluster from 16 clusters.

This algorithm starts as follows:

1. Presents at each dimension of FSLSM eleven questions; the total number of questions is 44.
2. From the learner's answers to each dimension question, the system will select one category from this dimension.
3. For example, the cluster (Active, Intuitive, Visual, Global) is written by summarizing the first two letters (A, I,Vi, G) and named this cluster with C1 cluster, the cluster (Reflective, Intuitive, Visual, Global) is written by summarizing the first two letters (R, I, Vi, G) and named this cluster with C2 cluster, and so on.
4. The last step at this phase is to discover the appropriate objects that match each LS cluster to be recommended to the learner at the next phase. The learner prefers to use some objects to learn using them [11].
5. For each cluster, the model determines the objects preferred by the learner at each category, as shown in Table 1.

Table 1: The objects preferred by the learner at each category by the Cluster C1

Categories of C1 Cluster	Objects preferred
Reflective	Videos ,PPTs ,PDFs, and Announcements
Intuitive	PDFs ,Videos ,PPTs , and Topic List
Verbal	PDFs , Videos, Announcements , and Email
Global	References, Assignments, Topic Lists, and Exercise

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Currently, cluster C1 has the objects (PPTs, Exercise, Announcements, PDFs, Videos, Email, Assignments References, and Topic List) that will be recommended to all learners belonging to the C1 cluster [11].

4.2 Recommending the Mapped Learning Objects to Each LS Cluster

The goal of this phase is to increase the LK by recommending the course objects based on the LS, followed by presenting all other material links as shown in figure 4, and give the learner a suitable time to learn before the pre-test.

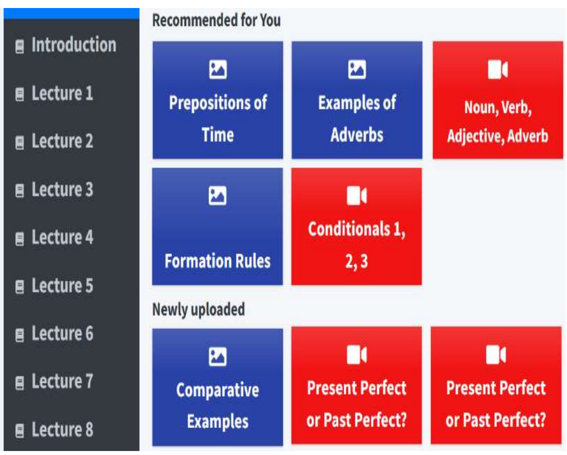

Figure 4: The recommend objects to the each LS combination

After this test, the model differentiates between the LMPs with the highest score and LMPs with the least score. The following two steps will describe the test steps in detail.

4.2.1 Preparing the pre-test

The domain model stores and maps the questions to each LMP, as shown in figure 3.

This model is a multi-level model that calculates and stores the marks, with a scale that starts from 0 up to 100; the main advance used is to mapping learner answers with each LMP. For example, the learner spent a certain period studying some LMPs and ready to solve the test.

The model calculates the value of each LMP knowledge level from the learner's answer. Subsequently calculates the course knowledge level. The following three equations are declared to determine the knowledge level for each course, depending on the test answers. As shown in Table 2.

Table 2: Three equations are declared to determine the knowledge level for each course

EQUATION	Description
$LMP_k = \sum_{i=1}^{m} mark_i$ (1)	The knowledge level for a specific LMP (Max score is 100) i- is the question number in the test m – the whole number of questions directed to the LMP mark – id the score on the question ,each question mark is (100/m)
$Unit_k = \frac{1}{n}\sum_{i=1}^{n} LMP_i$ (2)	The knowledge level for a specific unit i- is the LMP whole number in this unit n – the total number of LMP related to this unit
$Course = \frac{1}{z}\sum_{i=1}^{z} Unit_i$ (3)	The knowledge level for a the course i- is the number of units in this course z – the total number of units related to this course

Describes an example of a multi-level model the learner has a knowledge level of a certain course.

The knowledge level of each LMP was calculated by using (1), the summation of all scores of the correct questions answers related to it divided by the number of questions at this LMP, the number of questions at each LMP changes from one LMP to another and is definite by the course instructor.

Each unit KL was calculated by using (2), the summation of LMPs at this unit divided by the number of units, for example if the unit1 containing 3 LMPs with scores (75, 100, 80) then unit1 KL = (LMP1+LMP2+LMP3)/3 = (75+100+80)/3 = 85%.

The knowledge level of the entire course was calculated by using (3), the summation of all units divided by the number of it.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.2.2 Solving the pre-test

After the period of the learning, the learner starts to take and solve the first test and the proposed model discovers the entire KL for the learner. The learner can find the link to the test on his profile; can access the test by laptop or mobile. The test has a fixed period for all learners and the questions arise from the course test bank in a random way. The number of questions for beach LMP is selected by the course instructor; finally, the model stores each question score and the total score.

4.3 Recommending the Learning Objects to Each LS Cluster Based on the Knowledge Level

By the end of phase 2, each learner has scored at each LMP, and each LMP has some objects to declare it. The model will preview adaptive guidance at each learner profile page based on knowledge level, which recommends objects from the LMP that has the least scores at test 1. Each test is mapped with some LMPs, and the questions that have incorrect answers are directed to provide adaptive guidance to the learner to understand this LMP. Adaptive guidance changes after each test to adapt the time allowed to the learner before the next test. Finally, the learner takes the second test to measure the difference in KL.

5. EXPERIMENT AND RESULTS

By the start of 2020 up till now, COVID-19 makes the schools and universities decrease the study in physical groups and increase the study using online classes. It is recommended to design a real system of the proposed model for the English course of the Faculty of computer science, October 6 University.

The system was available for five weeks. 321 learners studied the online course, the first week: starts to collect data about the learner to initialize and create the Learner profile. Also, creates the domain model and discover The LS using the Ulearn questionnaire.

The system takes two weeks to recommend the course objects based on the LS, followed by presenting all other material links. At the end of this period, all learners take a pre-test. The system takes another two weeks to preview adaptive guidance at each learner profile page based on knowledge level, which recommends objects from the LMP that has the least scores at pre-test. Finally, the learner takes the post-test to measure the difference in KL.

The applied system results can be divided into 3 parts, the first part describes the LS results using the Ulearn questionnaire, the second part the relation between the number of correct answers mapped to each LMP at pre-test and post-test, and the final part is the effectiveness of the applied system.

5.1 Discover the LS using Ulearn Questionnaire.

The goal of discovering the LS is to increase the LK by recommending the course objects based on the LS, followed by presenting all other material links as shown in figure 4, and give the learner a suitable time to learn before the pre-test, 321 learners fill the questionnaire. The results are shown in figure 5.

For each dimension there are 321 learners were clustered into two categories. According to each category, each learner prefers to study using certain objects.184 active the other 137 learners are reflective, 190 sensitive the other 131 learners are intuitive, 244 visual the other 77 learners are verbal, and 215 sequential the other 106 learners are global.

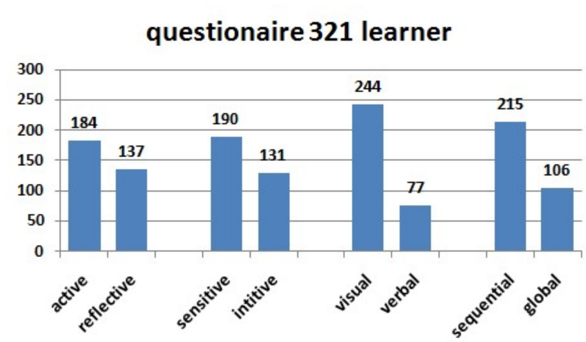

Figure 5: The Number Of Learners At Each Dimension Using Questionnaire

For each dimension there are 321 learners were clustered into two categories. According to each

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

category, each learner prefers to study using certain objects. 184 is active the other 137 learners are reflective, 190 sensitive the other 131 learners are intuitive, 244 is visual the other 77 learners are verbal, and 215 sequential the other 106 learners are global.

5.2 The Knowledge Level of Learners after Tests

To show the performance of the applied System, the 321 learners took two tests, both of them included the same 3 units with 9 LMPs (Present Perfect, Modal Verbs, and Conditional Sentences Type I, Conditional Sentences Type II, Conditional Sentences Type III, Present Simple, Present Continuous, Past Simple, and Past Continuous). The pre-test is performed after the training according to the LS and the second after our model.

After the pre-test, for all the learners, the system stored the number of correct answers mapped to each LMP, as shown in Table 3. The number of questions at each LMP is declared by the doctor and is not fixed. At this Table, each cell describes the number of correct answers to the total questions at this LMP.

Table 3 shows that the proposed system can discover that the learner XX715 not completely understand LMP1 and LMP5. So, the system presented adaptive guidance at each learner profile page based on knowledge level, which recommended the objects from LMPs that has the least scores at pre-test;

After the post-test, the system stored the number of correct answers mapped to each LMP as shown in Table 4, which has the number of correct answers (for the same learners from Table 3). At Table 4 each cell describes the number of correct answers to the total questions at this LMP, also Table 4 presenting the KL for each part of the course to examine if the KL increased after post-test or not.

The first 2 learners (Id XX715, and Id XX768) increased the number of correct answers at All LMPs compared with the pre-test. The learner (Id XX765, Id XX778, and Id XX298) increased the number of correct answers at some of the LMPs compared with the pre-test. The last 3 learners (Id XX997, Id XX932, and Id XX340)) increased the number of correct questions at some of the LMPs and decreased the number of correct questions at some of the LMPs. such as LMP1 at ID XX9977.

The KL for each LMP of the course is calculated to check if the KL increased after the post-test or not, The total numbers of learners at each LMP who have correct answers at the post-test compared with the pre-test are illustrated in Table 5.

From Table 5, the results can indicate that:

- After presenting the materials according to AERM-KLLS the Knowledge level increased at All LMPs.
- The number of Learners who has a full mark in LMP7 is 313 from 321 learners, indicating that this part is the most understood LMP
- The number of Learners who have a full mark in LMP6 is 283 from 321 learners, indicating that this part is still needed practice or another material.

5.3 Effectiveness of Applied System

The following tests are used to determine learning gain: a pre-test and a post-test. Except for the wording of several items, their order, and the multiple choice answers provided, the tests were linked and similar. Three professionals meticulously prepared and examined the exams, checking the wording of each topic and its associated multiple-choice responses, assessing content validity, and ensuring that the tests measured various learning capacities such as memory, understanding, and application. Furthermore, the tests were sufficiently reliable.

The experimental results show that from 321 learners, the knowledge level of 80 learners is elementary with a percentage of 25%, 61 learners are at the intermediate level with a percentage of 19%, 105 learners are at a very good level with a percentage of 33%, and 75 learners are at the advanced level with percentage 23%.as shown in figure 6.

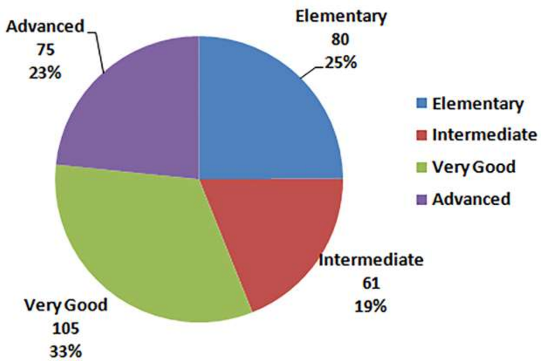

Figure 6: Learner's Knowledge Levels, After Pre-Test

The effectiveness of the applied system can be seen from the performance of the post-test score value at each level of the KL, as illustrated in Table 6.

Table 6: Proficiency level after the post-test

	Elementary 0-60	Intermediate 60-75	V.good 75-90	Advanced 90-100	total
The number of learners at pre-test	80	61	105	75	321
learners got marks on post-test more than or equal of pre-test	78	55	97	62	292
Percentage	97.5	90.1	92.4	82.7	90.97

At post-test 78 out of 80 got marks more than or equal of pre-test with 97.5%, the 90.1% of learners with an intermediate performance at pre-test got more marks or equal at post-test, the 92.4% of learners with Very good performance at pre-test got more marks or equal at post-test, and 82.7 % of the learners with high performance at pretest got more marks or equal at post-test. Overall performance is 90.97% at the post-test.

Table 7 describes also the effectiveness of the applied system from the performance of the post-test score values.

Table 7: Proficiency level after the post-test

	Elementary 0-60	Intermediate 60-75	V.good 75-90	Advanced 90-100	total
The number of learners at Pre-test	80	61	105	75	321
The number of learners at post-test	22	36	104	159	321

According to the results, in the pre-test, the total number of learners at the elementary level is 80 learners 24.9% of all learners (low knowledge level), and the post-test and the number of learners with elementary-level is 6.9% of total learners (22 out of 321).

In the pre-test, the total number of learners at the advanced level is 75 learners from the 321 learners but at the post-test is 159.which means that the applied system increased the number of learners at high KL and decreased the number of learners at low KL.

Comparing these results to the paper of an adaptive learning system based on knowledge level for English learning [15]. Figure7 shows the difference between proficiency level between the pre-test and post-test. The elementary level was decrease from 58% in pre-test to 22% on the post-test. For the intermediate level, there was an improvement from 37% to 56%.

For advance knowledge level, there is also an increment from 5% to 22%.

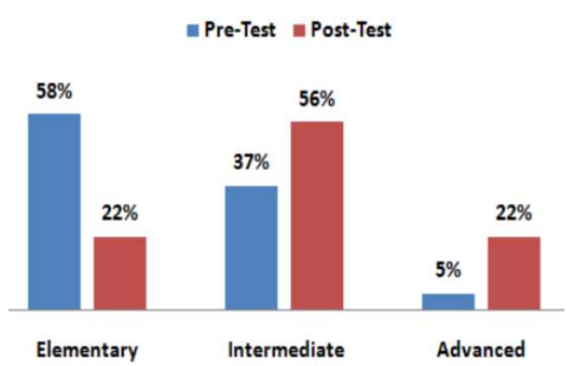

Figure 7: shows the difference between proficiency level between the pre-test and post-test[15].

6. CONCLUSION AND FUTURE WORK

The proposed adaptive e-learning recommendation framework contains major components required in order to produce the adaptation. It is a conceptual model which can be used as a basis to design and develop a wide range of adaptive e-learning systems. Specific instances of the framework may adopt different perspectives on the domain model, learner model, and adaptation model.

In this paper, an adaptive e-learning system called AERM-KLLS has been designed as an instance of the framework. It takes into account two main learner characteristics – LS and LK, in order to recommend the most needed and suitable objects. The knowledge level is used to construct personalized learning paths at the level of both instructional units and LMP. It is also used to provide adaptive guidance, such as supplying relevant additional content, offering recommendations on what to study, suggesting the sequence of study, and offering feedback on learning progress. The proposed model gives promising results with an overall accuracy is 90.97% at the post-test, 159 learners from the 321 learners got marks more than 90% of the full mark of posttest, and 22 learners from the 321 learners still at the elementary level.

The future work is Increasing the interaction between the learner and the course, which is also required to be enhanced during the learning process “to give the feel of the classroom where learners informally interact with one another. And Trying to adapt the course content to the learner having different interests, knowledge background, learning style, etc. At the e-learning environment.

REFRENCES

[1] 301. M.N. Doja, “An Improved Recommender System for E-Learning Environments to Enhance Learning Capabilities of Learners,” In Proceedings of the ICETIT 2019, Springer: Cham, Switzerland, vol. 605, pp. 604–612, 2020. http://doi.org/10.1007/978-3-030-30577-2_53

[2] 302 A. S. Aziz, S. A. Taie, and R. A. El-Khoribi,” The Relation between the Learner Characteristics and Adaptation Techniques in the Adaptive E-Learning Systems,” In: Proceedings of the International Conference on Innovative Trends in Communication and Computer Engineering (ITCE), Aswan, Egypt, pp. 76-81, 2020. http://doi.org/10.1109/ITCE48509.2020.9047766

[3] 303 G. Siemens and R.S.J.D. Baker, “Current state of learning analytics and educational data mining,” Educause Learning Initiative (ELI), pp. 1–38 , 2013.

[4] 304 E. Gomede, R.M. De Barros, and L.D.S. Mendes, “Use of Deep Multi-Target Prediction to Identify Learning Styles,” Appl. Sci., vol. 10, no. 5, pp. 1756, 2020. https://doi.org/10.3390/app10051756

[5] 305 C. Troussas, A. Krouska, C. Sgouropoulou and I. Voyiatzis, “Ensemble Learning Using Fuzzy Weights to Improve Learning Style Identification for Adapted Instructional Routines Entropy,” Entropy, vol. 22, no. 7, pp. 735-751, 2020. https://doi.org/10.3390/e22070735

[6] 306 M. Hamada, and M. Hassan, “An Enhanced Learning Style Index: Implementation and Integration into an Intelligent and Adaptive e-Learning System,” EURASIA Journal of Mathematics, Science and Technology Education, vol. 13, no. 8, pp. 4449-4470, 2017. https://doi.org/10.12973/eurasia.2017.00940a

[7] 307 RAJI, Mohammad, DUGGAN, John, DECOTES, Blaise, et al. “Visual progression analysis of student records data”, IEEE Visualization in Data Science (VDS). IEEE, pp. 31-38, 2017. http://doi.org/10.1109/VDS.2017.8573447

[8] 308 B. Ciloglugil, "Adaptivity based on Felder-Silverman Learning Styles Model in ELearning Systems," 4th International Symposium on Innovative Technologies in Engineering and Science (ISITES 2016), pp. 1523-1532, 2016.

[9] 309 S. EL Janati, A. Maach, and D.ElGhanami, “Learning Analytics Framework for Adaptive E-learning System to Monitor the Learner’s Activities,” International Journal of Advanced Computer Science and Applications, vol. 10, no. 8, pp. 275-284, 2019. http://doi.org/10.14569/IJACSA.2019.0100835

[10] 310 S. Bhaskaran, R. Marappan, and B. Santhi, “Design and Comparative Analysis of New Personalized Recommender Algorithms

with Specific Features for Large Scale Datasets," Mathematics 2020, vol. 8, no. 7, pp. 1106, 2020. http://doi.org/10.3390/math8071106

[11] 311 A.S Aziz, R. A. El-Khoribi, and S. A. Taie, "AFCM Model to Predict the Learner Style Based on Questionnaire and Fuzzy C Mean Algorithm," Journal of Theoretical and Applied Information Technology (JATIT), vol.99, no. 2, pp. 343-357, 2021.

[12] 312 A. Paramythis, and S. Loidl-Reisinger, "Adaptive Learning Environments and eLearning Standards," EJEL, vol. 2, no. 1, pp. 181-194, 2004.

[13] 313 M. Gokalp, "The effect of students' learning styles to their academic success," Creative Education, vol. 4, no. 10, pp. 627-632, 2013.

[14] 314 S. Nafea, F. Siewe, and Y. He, "Ulearn:personalised learner's profile based on dynamic learning style questionnaire", in IEEE Technically Sponsored Intelligent Systems Conference (IntelliSys), London, vol. 8, no. 12, pp.842-847, 2018. https://doi.org/10.1007/978-3-030-01057-7_81

[15] 315 S. Sfenrianto, Y. B. Hartarto, H. Akbar, M.Mukhtar, E. Efriadi, and M. Wahyudi, "An Adaptive Learning System based on Knowledge Level for English Learning," International Journal of Emerging Technologies in Learning (iJET), vol. 13, no.12, pp. 191–200, 2018. https://www.doi.org/10.3991/ijet.v13i12.8004

[16] 316 P. Brusilovsky, and E. Millán, "User models for adaptive hypermedia and adaptive educational systems," In: P. Brusilovsky, A. Kobsa and W. Neidl (eds.): The Adaptive Web: Methods and Strategies of Web Personalization. Lecture Notes in Computer Science, vol. 4321, Berlin Heidelberg New York: Springer Verlag, pp. 3-53. 2007.

[17] 317 Y. Zhou, C. Huang, Q. Hu, J. Zhu, and Y. Tang," Personalized learning full-path recommendation model based on LSTM neural networks," Information Sciences, vol. 444, pp. 135–152, 2018. https://www.doi.org/10.1016/j.ins.2018.02.053

[18] 318 S. M. Nafea, F.Siewe, and Y. He, "A novel algorithm for course learning object recommendation based on student learning styles," In Proceedings of the IEEE International Conference on Innovative Trends in Computer Engineering (ITCE), Aswan, Egypt, pp. 192–201, 2019. https://www.doi.org/10.1109/ITCE.2019.8646355

[19] 319 M. S. Hasibuan, L. E. Nugroho, and P. I. Santosa," Model detecting learning styles with artificial neural network," Journal of Technology and Science Education JOTSE, vol. 9, no. 1, pp. 85-95, 2019.

[20] 320 T. Sheeba, and R. Krishnan, "Automatic Detection of Students Learning Style in Learning Management System," In Smart Technologies and Innovation for a Sustainable Future, Advances in Science; Springer International Publishing: New York, NY, USA, pp. 45–53, 2019. https://www.doi.org/10.1007/978-3-030-01659-3_7

[21] 321 A. Jalal, and M. Mahmood, "Students' behavior mining in e-learning environment using cognitive processes with information technologies," Education and Information Technologies, vol. 24, no. 5, pp. 2797-2821, 2019.

[22] 322 M. A. Abdullah, " Learning style classification based on student's behavior in moodle learning management system," Transactions on Machine Learning and Artificial Intelligence, vol. 3, no. 1, pp. 28-40, 2015.

[23] 323 K. a. Almohammadi, A. Alzahrani, D. Alghazzawi, and G. Aldabbagh, " A type-2 fuzzy logic recommendation system for adaptive teaching," Soft Computing, vol. 21, no. 4, pp.965–979, 2017 http://doi.org/10.1007/s00500-015-1826-y

[24] 324 C. Troussas, K. Chrysafiadi, and M. Virvou, "An intelligent adaptive fuzzy-based inference system for computer-assisted language learning," Expert Systems with Applications, vol. 127, pp. 85–96, 2019. http://doi.org/10.1016/j.eswa.2019.03.003

[25] 325 S. Kolekar, R. M. Pai, and M. M.Pai, "Prediction of learner's profile based on learning styles in adaptive E learning system, " iJET , vol. 12, no. 6, pp. 31-51 , 2017. https://doi.org/10.3991/ijet.v12i06.6579

[26] 326 D.H. Hassouna, A. E. Khedr, A.M. Idrees, and A. I. Elseddawy, "Intelligent Personalized System for Enhancing the Quality of Learning," Journal of Theoretical and Applied Information Technology (JATIT), vol.98, no. 13, pp. 2199-2213, 2020.http://doi.org/10.35741/issn.0258-2724.98.13.1

[27] 327 Z. Ghaedi, and B.Jam, "Relationship between Learning Styles and Motivation for Higher Education in EFL Students", Theory

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and Practice in Language Studies, vol. 4, no. 6, pp. 1233-1235, 2014.

[28] 328 M. P. Liyanage, L. G. KS, and M. Hirakawa, "Detecting learning styles in learning management systems using data mining," Journal of Information Processing, vol. 24, no.4, pp. 740–749, 2016. http://doi.org/10.2197/ipsjjip.24.740

[29] 329 F. Essalmi, "Generalized metrics for the analysis of E-learning personalization strategies," Computers in Human Behavior, vol. 48, pp. 310-322, 2015.

[30] 330 H. M. Truong, "Integrating learning styles and adaptive e-learning system: Current developments," problems and opportunities - Computers in human behavior, Elsevier, vol. 55, Part B, pp. 1185-1193 , 2016. https://doi.org/10.1016/j.chb.2015.02.014

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

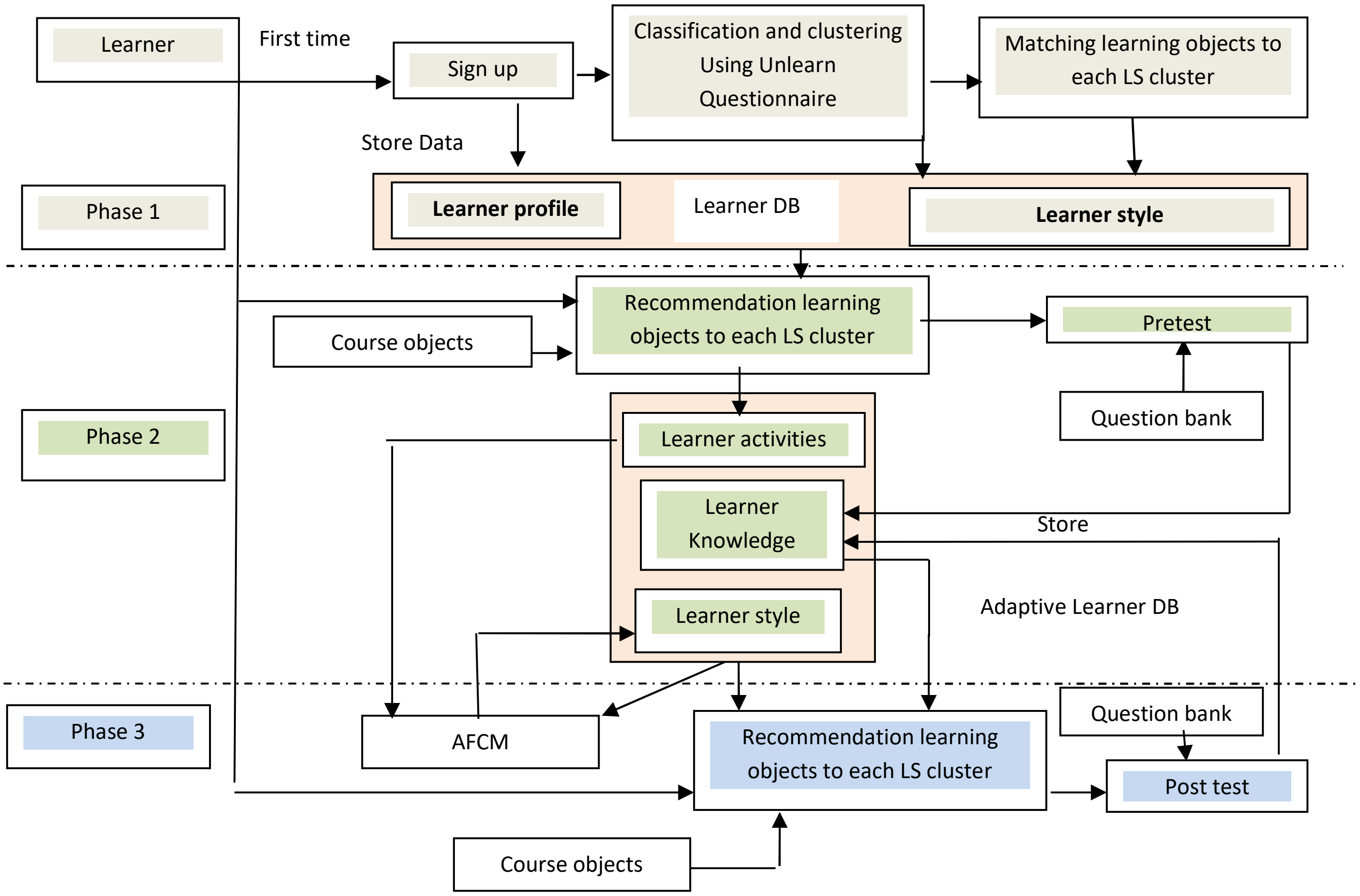

Figure 2: AERM-KLLS Model framework.

Table 3: The sample of 8 learners describing the number of correct answers mapped to each LMP.

ID	LMP1	LMP2	LMP3	LMP4	LMP5	LMP6	LMP7	LMP8	LMP9	correct answers
XX715	3/5	1/1	1/1	1/1	0/1	1/1	1/1	2/2	2/2	12
XX768	2/5	1/1	0/1	1/1	1/1	0/1	1/1	2/2	½	9
XX765	3/5	0/1	0/1	1/1	1/1	1/1	1/1	2/2	2/2	11
XX778	1/5	1/1	1/1	1/1	1/1	0/1	1/1	1/2	2/2	9
XX298	1/5	1/1	1/1	0/1	0/1	0/1	0/1	2/2	2/2	7
XX997	5/5	1/1	1/1	1/1	0/1	1/1	0/1	0/2	2/2	11
XX932	2/5	1/1	0/1	0/1	1/1	0/1	1/1	2/2	2/2	9
XX340	2/5	0/1	1/1	1/1	0/1	1/1	0/1	2/2	1/2	8

Table 4: Sample of 8 learners describing the number of correct answers mapped to each LMP after post-test

ID	LMP1	LMP2	LMP3	LMP4	LMP5	LMP6	LMP7	LMP8	LMP9	correct answers
XX715	4/5	1/1	1/1	1/1	1/1	1/1	1/1	2/2	2/2	14
XX768	5/5	1/1	1/1	1/1	1/1	1/1	1/1	2/2	2/2	15
XX765	3/5	1/1	1/1	1/1	1/1	1/1	1/1	2/2	2/2	13
XX778	4/5	1/1	0/1	1/1	1/1	1/1	1/1	1/2	2/2	12
XX298	5/5	1/1	1/1	1/1	0/1	0/1	1/1	2/2	2/2	13
XX997	4/5	1/1	1/1	1/1	1/1	1/1	1/1	1/2	2/2	13
XX932	3/5	1/1	1/1	1/1	1/1	1/1	1/1	2/2	1/2	12
XX340	4/5	1/1	1/1	0/1	1/1	1/1	1/1	2/2	2/2	13

Table 5: Total number of learners who correct questions to All LMPs

	LMP1	LMP2	LMP3	LMP4	LMP5	LMP6	LMP7	LMP8	LMP9
Learners has full mark at Pre-test	251	209	239	257	251	222	258	210	246
Learners has full mark at post-test	304	289	299	308	299	283	313	293	307