

# Modeling an Adaptive e-Learning System for Improved Learning Performances

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## ABSTRACT

In majority of the online learning systems in use today, lack proper integration of adaptive, collaborative, personalized and ubiquitous concepts in their design and implementation. Integration of these basic concepts in online learning systems will enable adaptation, individualization, and collaboration of learning resources to learners' preferences, with an added advantage of accessibility to online resources anywhere and any time. Hence, the research proposes an Adaptive E-Learning System (AES) model that incorporates activities sequencing in a personalised, adaptive, collaborative and ubiquitous learning environment. The system model consists of the system (software) architectural diagram and mathematical model of activity sequence. The design is presented using the UML activity diagram and the class diagram. The full implementation of the system is currently being carried out and is being tested with real life cases..

## General Terms

Adaptive learning, e-learning, Learning Style.

## Keywords

Personalised learning, Ubiquitous Learning, Affective Learning, Context-Aware.

## 1. INTRODUCTION

Technological advancement in educational system has opened up diverse innovations to teaching and learning. This has led to transforming the role and activity of both the teachers and the students in an institutional based teaching and learning community; and creating an environment for technology-driven and student-centric control platform. The availability of electronic devices (such as, mobile phones, wearable computers, sensors, and Radio-Frequency Identification (RFID) cards), and high speed internet connection has created a new opportunities to embed in everyday life a personalised learning activities. Mostly, the current trend of e-learning system development is connecting the technology with the fundamental principles of learning theories, learning styles, strategies and approaches that will lead to students' motivation to actively engage in learning process and promote their study and learning outcome performances.

After the initial impact of computing in education, the introduction of e-learning manifested the continuous transformations that were occurring in education. The grasp of ubiquitous computing (U-learning) in education marks another great leap, with U-learning emerging through the concept of ubiquitous computing. U-learning is both persistent and pervasive, allowing students to access education seamlessly. U-learning has the capability to change education and remove

many of the constraints of traditional learning. However, providing a one-size-fit-all learning content to learners can lead to cognitive mismatch. Providing difficult learning objects to learners with low online activities performance and providing redundant tasks to learners with high online activities performance is also known as cognitive mismatch. The integration of adaptive learning with ubiquitous computing offers great innovation in the delivery of education, allowing for personalisation and customisation to learner needs.

Context-awareness differentiate U-learning from other types of learning and is therefore considered a major characteristic by researchers, whereas permanency, accessibility, immediacy and interactivity are named common characteristics in the literature. The application of this major characteristic in technology-enhanced learning systems was enabled by the use of mobile, wireless communication and sensing technologies, and it has led to the development of new learning environments that can remove the learning space limitations of the classroom, can provide personalised learning guidance and can support learning in real-world contexts. This new u-learning approach has been called context-aware ubiquitous learning [10].

The concept of ubiquitous context-awareness in learning emphasises the features of learning the exact content at the right place and time, and also to facilitate the process that support learning without any time or place constraint in a seamless ubiquitous learning framework [12]. Context-awareness in ubiquitous learning requires the detection of learner information and provides learners with various learning content through their mobile devices based on different learning contexts [16]. [8] proposed different types of contextual information, which include location, activity, time and identity for building context-aware applications. In order to determine learner location, a global positioning system (GPS) detects learner location where the GPS receiver simultaneously senses the location of at least three minimum satellites in outdoor environments using the triangulation model [2].

Wireless Local Area Network (WLAN) when compared with GPS provides more accurate location information for both indoor and outdoor environments. It has been widely used mostly in public school environments [11]. WLAN positioning is a more suitable method of enabling the development of context-aware ubiquitous learning that can provide learning content associated with learning contexts and assists learners in context-based learning in a campus environment.

According to [7], assisting learners to learn precise content at the right place and time has proven to be a difficult task. It includes setting the learning activities in respect to the features of learning contents, learner's personalisation and considering the real-world into account. Without a proper guidance plan

using appropriate strategies and supporting tools, the performance of learners could be affected significantly. Therefore, the need to develop an effective and efficient personalised adaptive u-learning framework for learners learning paths is of great importance.

In ubiquitous learning framework for personalised adaptive system, a sequenced learning content is personalised due to cognitive mismatch. Learning content adaptation based on the learners needs, and personalisation of learning contents enables the learning system to work with learners of different features anywhere and anytime.

In order to improve the performance of a personalised ubiquitous learning system, the online behavioural characteristics of the learners is also considered during personalisation the learning content. The benefit of a student's online behavioural component in learning has led to the inclusion of learners' affective states in the learner's models. The consideration of using online behavioural characteristics has led to the achievement of a higher learning outcomes in intelligent learning system.

The behavioural attributes widely used in the research of an affective computing for an intelligent learning system include features such as boredom, confusion, concentration and delight. This research work focused on the negative behavioural states such as frustration and boredom. To include the behavioural states in the student model, learners behavioural attributes are identified then responded to when the learners are interacting with the personalised adaptive ubiquitous learning system.

Several methods have been used to detect learners' behavioural attributes which include observation, learners' personal log of their behavioural attributes, System log file of learners learning path, affective states modelling, Sensing using physiological sensors, emotion attributes using facial recognition method and data analyses using physical sensors [15]. Two responses to affective states in personalised adaptive ubiquitous learning system are: (i) Addressing what led to frustration by adapting the learning content; and (ii) encouraging learners to create new goals and avoiding negative consequences by showing motivational messages. In this research frustration will be responded to by providing motivational messages.

With student-centred, personalised learning, students' unique needs can be identified and addressed. This is about optimising day to day learning and maximising the time spent on learning. Learners also get a collection of badges that verify the stages of their learning.

Personalised learning can be define as the methods of streamlining learning for based on individual learner's strengths, interest and their needs thereby enabling the learners voice and choice of how, what, when and where they learn. This provides flexibility that ensures mastery of the highest standards. Having individual learning style is a key part of personalised learning which is very essential in education. For a personalised learning, it is important for the facilitator to meet individual learner within their own zone of proximal development. This will help to fill the gap between the individual student and their learning, and also support their learning interest for them to succeed.

The development in personalisation has led to several the dynamic changes between the facilitator and learner. Educators can take several roles such as coaches, mentors, teachers, and facilitators. Also by giving learners power over their learning process in their interests and passions, they feel in control and motivated.

Schools are no longer seen as physically confined spaces with classrooms, tables, desks, chairs and a teacher dishing out instructions and reading out notes in front of students which in most cases involve a one-size-fits-all model using a single textbook. But it can now be seen as learning anytime and anywhere thereby bridging formal and informal learning experiences connected through the effective use of educational technologies. Combining the modalities of digital learning with competency-base progressions has proved fundamental in modernizing educational system to meet individual learners' styles. Meeting individual learning includes the idea of Connectivism, where learners have flexible learning environments using a variety of objects, resources and modalities to facilitate learning.

Adaptive learning has been hailed as an alternative approach to learning and offer great advantages in providing learners with personalised and specific knowledge when needed. There by improving learning outcomes of learners by handling the diverse learning needs of individual students.

Combining the advantages of adaptive learning environment with ubiquitous learning environment provides the benefits of mobile devices flexibility and ubiquitous computing. Learners are given the free will to learn at any particular place an time within a learning environment which offers adaptability and personalisation as well as the flexibility and obstructive learning.

Adaptive learning can be defined as changing learning processes while considering the learners learning style and preferences. Adaptive learning includes the learning styles of individual learners which makes him/her unique.

Many teachers, system developers and learning technologists have put great efforts in the development of teaching and learning process, and modules towards a dynamic learning framework. Adaptive learning systems provides high number of features such as learner preferences, learning materials and learning interest to provide personalised learning services.

For modern services that eases people' lives, localisation of devices has become a critical aspect. Outdoor and indoor localization have been researched into by various researchers worldwide in order to determine precise location. To provide an accurate location information, Global Positioning System (GPS) and Global Navigation Satellite System (GNSS) were built. Also, to develop the area of Internet of Things (IoT), a reliable indoor localization is needed. Both Indoor and Outdoor localization require sensors that are part of the IoT to benefit from accurate indoor localisation.

Both Outdoor and Indoor localisation paved way for new possibilities of digital services and products. Location-awareness in mobile application have proved more beneficial especially from indoor location information. The infrastructure for IEEE 802.11 technologies is widely available in various buildings (both residential and business). GPS is considered as one of the most widely used Outdoor sensing technology, but it has several setbacks that make GPS difficult to be used as an indoor positioning system. With the need for a line-of-sight between the receivers and the satellites, and customized hardware, there is low accuracy and poor indoor coverage. Also, the GPS accuracy is affected by the interference and noise sources within the environment.

Another important alternative that has proved effective in indoor positioning systems is the usage of IEEE 802.11 wireless local area networks. The use of WLAN cannot be out

rightly considered as a direct way of positioning because of the purpose and design. However, part of the characteristics and properties of WLAN signals can be used to calculate asset position. Signal Strength (SS) is considered as one of the most common indicator of the signal received from an Access Point. Several signal strength models have been used for estimation of position in WLAN environments.

The current processor speed of simple computer units, and the increasing capabilities of wireless technology, there more accuracy than before the possibility of localising images and people remotely within a predefined time frame. An example of an indoor localisation methodology based on WLAN is the Received Signal Strength Indication (RSSI). RSSI data provided are unsteady and complex of their multi-path propagation in sophisticated indoor areas and even though it is not made as a location sensor, they provide enough position calculation of a given asset. Also, the RSSI based systems do not need any provisional hardware to the existing WLAN infrastructure.

## **2. RELATED WORKS**

Several research works have been conducted in the field of learning technologies, ubiquitous computing with respect of adaptive and personalised learning. Also, many private and public institutions have successfully deployed online educational packages for their learning activities.

[22] presented a Context Aware Ubiquitous Learning Environment for Peer-to-Peer Collaborative Learning. The research motivation was based on past learning systems that are either centralized server based or based on client-server architecture. The objective was to fully support peer-to-peer collaborative learning and make use of a context model such as context acquisition mechanism, collection of contextual information to build a context-aware ubiquitous learning system. The result shows that the system fully supports the needs of peer-to-peer collaborative learning. The limitation is that even if a peer can serve as both client and server there is a need to create a learning path effective learning.

[23] also presented a personalized adaptive content system for context-aware mobile learning. The research was motivated by the fact that most learning contents designed for desktop platforms are not suitable for mobile devices. Also, some materials are not relevant to learner's preferences which in turn affect the learning efficiency and also increase the cost of communication. The research provides adaptive contents based on device capabilities and learner's preferences. The limitation is that the system was not implemented based on real-time learning system to evaluate the features in ubiquitous learning environment.

[5] presented a design of an adaptive e-learning model based on learner's personality. The motivation is to address the problem of frustration and dissatisfaction experienced by online learners when presented with massive amount of contents. The objective of the research work was to suggest new teaching strategies on e-learning context using learner's personality based on the Myers-Briggs Type Indicator model. Result shows that placing the learner beside an appropriate learning style and matching them with their preferences leads to improvement and makes the online learning environment more enjoyable. The evaluation shows that changes in learners' preferences on real learners were not achieved.

[7] presented a knowledge engineering approach to developing mind tools for context-aware ubiquitous learning. The research

motivation is based on the inadequacies of the learning tools to guide and assist learners to learn in a complex learning situation. The objective of the research is to actively provide personalised guidance and hints to respective learners by interacting with them through their learning gadget. The method used involves use of mind tools for innovative learning scenarios using innovative model and mobile knowledge constructor model. Result shows that the innovative model helps improves learners classification and comparison ability. The system designed failed to add to its features a collaborative learning model which has been known as an integral part of effective learning.

[14] presented the use of quick response codes in the classroom with the objective of exploring and analysing teaching methods and processes. Quick Response (QR) codes can be incorporated into mobile devices and used in the classroom. The approach involves the implementations of QR codes model in an educational context. The result shows that QR codes model provides support for both independent and collaborative learning and can motivate and engage learners. However, the system does not consider the pedagogical aspect of learning into account. It mainly focuses on technology and the most of the activities are not well-planned.

[10] developed a web 2.0-based ubiquitous learning platform for schoolyard plant identification. Rapid progress of wireless communication, sensing technologies, and mobile application development that has enabled learners to learn in an environment by combining learning from both synchronous and asynchronous scenario formed their motivation. The objective of the research shows a new way of using technologies in a u-learning environment. The system made use of android phone, sensing technology, and web 2.0 environments. It only shares learners' notes and observation among other learners without any interaction between them and also does not adapt learner style.

[15] presented a system called a Mobile Learning Content independent Versatile Ubiquitous System (CIVUS), which was designed to facilitate collaborative creation of content, management, organization, and control of publication of documents in a centralized environment. It a m-learning system that renders personalised contents to the learner. The system promotes communication between learners and the facilitators by encouraging learners to share self-made multimedia contents. The system is based on one-size-fit-all and requires collaboration to be effective.

[13] presented an adaptation to learners' learning styles in a multi agent e-learning system which addresses the issue of the adaptation that formed the motivation for the work. The research described the learning objects as well as the learning and their learning styles and makes use of semantic web with intelligent agents. The result shows a high precision in detecting learning styles and in delivering learning materials. The system works conveniently but only helps in personalised learning, and for learners to effectively learn, collaborative method of learning needs to be adopted.

[6] presented a ubiquitous learning environment using android mobile application. The need to address the problem of gaining and retaining the motivation of learners in any e-learning environment formed the bases of the research. The system is an android-based e-learning environment used to adapt to the learning style of the learners. The system made use of ARCS model and relevant learning pedagogy in its design. The result

of the application shows that the system can translate some of its principles into concepts applicable to mobile learning. The design is not cross-platform and its effectiveness and efficiency were not tested.

[4] developed an adaptive e-learning application architecture based on IEEE LTSA reference model. There is a need for non-provision of sufficient guidelines for e-learning designer. To assist instructional designers in efficiently developing adaptive e-learning system based on the IEEE LTSA Models, the work consists of the development of an architectural design of a learning management system using UML Diagram. The result of the application identifies the problem of currently deployed web architecture models and explores an efficient and practical solution. The model does not consider the different channel perception of learning that can assist in achieving an effective collaboration.

[1] presented a cognitive load theory-based framework for designing an e-learning environment. The objective was to suppress the complexity of learning contents while considering the interactivity elements to avoid cognitive overload on the part of learners. The framework emphasized the significance of cognitive load theory to instructional design and procedure in an e-learning environment. Individualised learning was the focus and does not handle collaborative learning.

[21] developed a learner model for automatic detection of learning Style using fuzzy cognitive map (FCM) in adaptive e-learning system. The need to optimize and facilitate learners' interaction using a web-based educational system formed their motivation. The system used Felder Silverman Learning Style Model (FSLSM) to model approach that automatically identify student's learning style in learning systems. The system used FCM model for identifying learning style and individualise learners' according to their needs. The results shows a high precision value signifying that student learning style can be detected. The system fails to capture complete learners profile and tailored only to personalized environment.

### **3. MODELING THE ADAPTIVE E-LEARNING SYSTEM**

#### **3.1 System Architecture**

The system model in figure 1 shows the software architecture of the system consisting of key components: Learner Interface

(AES portal, including Pre-test sub module), Ubiquitous Module (WLAN, QR Code), Learner Profile module, Learning Activities Management Module (collaboration, evaluation, offline services, etc.), Adaptation Module, Learning Content Analyzer Module and Database Systems, all interconnected for effective communication of data among components.

The learner interface module is made up of a login section, registration section and pre-test section that help to manage the learners profile and preferences. The learner interface module uses the learners' model which helps to the system in sorting out the knowledge space, cognitive characteristic, learning style, and preferences of individual learners. The system make use of a content analyser module which consist of the concept and content selection rules to interpret the adaptation rules specified by the adaptation model. The content analyser module also helps in aligning the learning goals and the domain concept ontology to create individual learners' personalised learning paths. The adaptation module contains the rules for selecting the content and concept for individual learning path. Educational resources model is used to select appropriate resource for the adaption model and creating learners content while selected concepts are retrieved from the domain model.

The Learning Activities Management module consists of collaboration sub-module which uses the an adaptation ruler parser, a model for activity sequence, and a model for behavioural tracker. The model for activities sequence groups the learners activities according to the behavioural tracker model and adaptation rule. The data synchronization of both online and offline server helps to update, replicate and mirror the online server for seamless activities. Evaluation sub-module uses the Evaluation model to handle all forms of assessment.

Ubiquitous module uses the ubiquitous model which made learning synchronous and asynchronous. Among the synchronous part using WLAN is the location request for learners location from terminal and calculation of their position by making use of available Access Point (AP) wireless signal strength through their mobile devices. The asynchronous part is the use of QR Codes by learners to interact with the learning objects already embedded in learning system through their mobile devices.

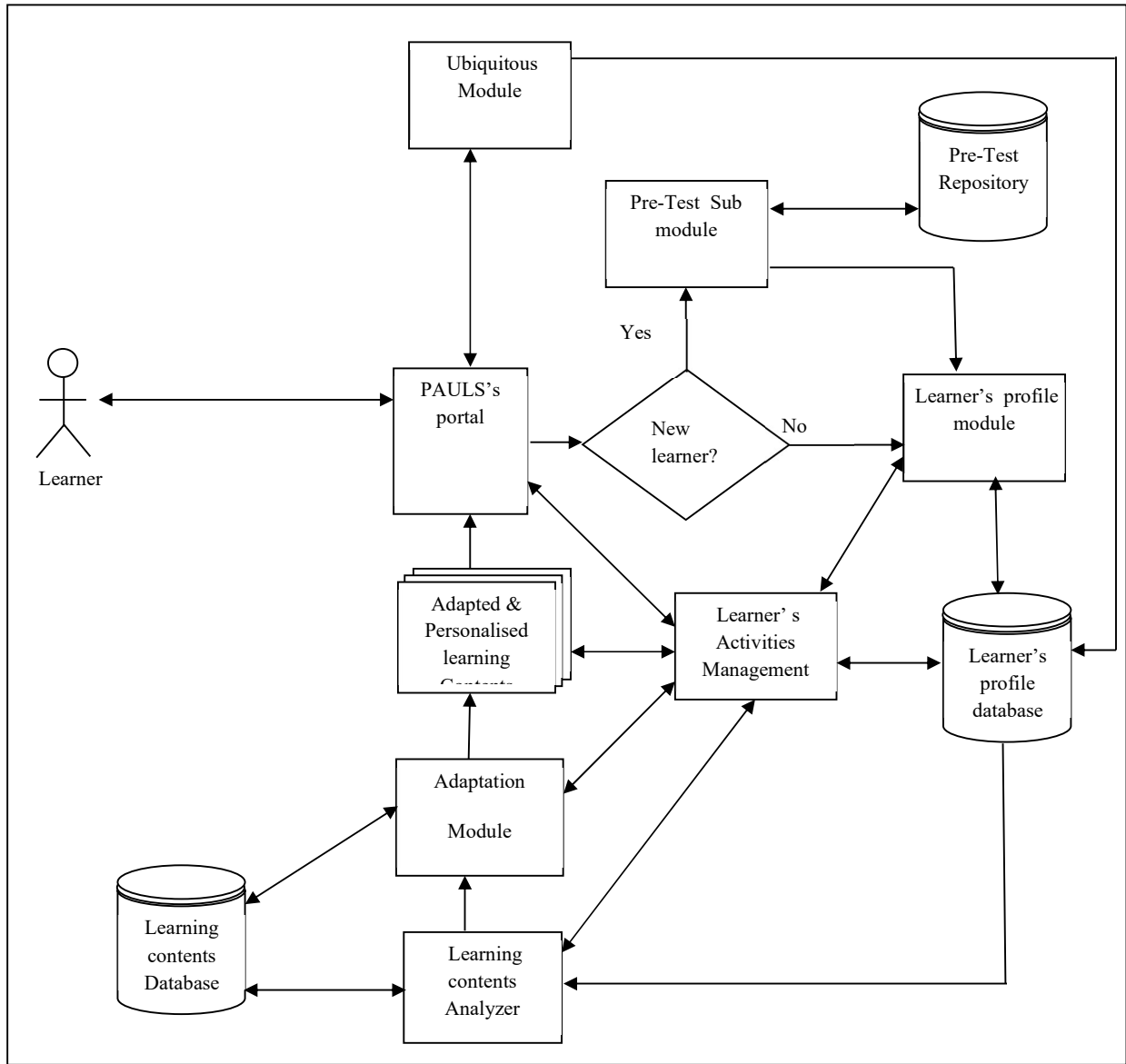


Figure 1: An Adaptive E-Learning System (AES) Model

### 3.2 Mathematical Modelling of Activity Sequence in AES

#### Mathematical Modeling of Activity Sequence in AES

The mathematical model shows a model of activity sequence in the Adaptive E-Learning System. The model designed adopted and adapted the following under listed techniques sequentially:

- a. Learners' location detection: the use of location based Received Signal Strength (RSS) and fingerprinting algorithm is employed. The positioning system methods on WiFi using RSS are divided in two: trilateration algorithm and fingerprinting technique. The trilateration algorithm helps estimates the target position and the fingerprinting technique is used to get the target location by matching the fingerprint information [17], [19]. Trilateration Algorithm calculates the coordinates based on geometry and find the intersection of three spheres involved as shown in the quadratic equations.

The simplified geometric algorithm must have at least three anchor nodes, must be known and the distance estimated from a node. The coordinates of the three anchor nodes  $A_1$ ,  $A_2$ , and  $A_3$  are known in advance as  $(X_{a1}, Y_{a1})$ ,  $(X_{a2}, Y_{a2})$ ,  $(X_{a3}, Y_{a3})$  and the distances from these three anchor nodes to node A are  $d_{a1}, d_{a2}, d_{a3}$ . The coordinates of node A  $(x, y)$  are unknown, then formulae in equation 1 is stated as follows [18]:

$$\begin{aligned}
 d_{a1} &= \sqrt{(x - x_{a1})^2 + (y - y_{a1})^2} \\
 d_{a2} &= \sqrt{(x - x_{a2})^2 + (y - y_{a2})^2} \\
 d_{a3} &= \sqrt{(x - x_{a3})^2 + (y - y_{a3})^2}
 \end{aligned}
 \tag{1}$$

To calculate the coordinates, the equation (1) was used to derive equation (2)

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2(x_{a1} - x_{a3}) & 2(y_{a1} - y_{a3}) \\ 2(x_{a2} - x_{a3}) & 2(y_{a2} - y_{a3}) \end{bmatrix}^{-1} X \begin{bmatrix} x_{a1}^2 - x_{a3}^2 + y_{a1}^2 - y_{a3}^2 + d_{a1}^2 - d_{a3}^2 \\ x_{a2}^2 - x_{a3}^2 + y_{a2}^2 - y_{a3}^2 + d_{a2}^2 - d_{a3}^2 \end{bmatrix} \quad (2)$$

The three APs are centers respectively and are used to locate the target point using the trilateration algorithm. The distances between the corresponding APs and the target are seen as the radiuses of three circles while the intersection of the three circles is the target point.

RSS model for location fingerprinting is based on statistical theory and proven industry practice. Location fingerprinting techniques match the fingerprint of some characteristic of a signal that is location dependent. The received specific RSS comprises of existing data in the database. The position of the learner is calculated based on the matching algorithm while the  $K$ -Nearest Neighbour (KNN) algorithm is used to match data in fingerprinting system [19]. The unknown position of learners is determine using the fingerprint map through KNN methods. This algorithm considers  $K$  calibration points (CPs) to get the approximate position of the target. The essence is to compare the fingerprints in the fingerprint map to the observed measurements and to select  $K$  calibration points with the “nearest” RSS values as shown in equations (3) and (4) respectively.

$$L_K^2 = \{P_1, P_2, P_3, \dots, P_K\} \quad (3)$$

where  $L_K^2$  is the calibration point coordinates corresponding to the list of  $K$  number of fingerprints.

$$\bar{a}_{1:k} = \{\bar{a}_1, \dots, \bar{a}_k\} \quad (4)$$

Which satisfies

$$d(\bar{y} - \bar{a}_1) \leq d(\bar{y}, \bar{a}_1), \text{ where } \bar{a}_i \in \bar{a}_{1:k}, \bar{a}_j \in \bar{a}_{1:k} \text{ and the function } d(\cdot) \text{ is a picked distance measure.}$$

The most common choice as a learner’s location estimator  $\hat{x}$  is the average of the coordinates of the  $K$  “nearest” fingerprints as in equation (5):

$$x = \frac{1}{k} \sum_{i=1}^k P_i, P_i \in L_{1:k} \quad (5)$$

The estimator is used to compute the location estimation, because the number of possible estimates is always finite and is a function of the number of CPs. The value of  $K=1$  is used to estimate the location, which leads to the Nearest Neighbour (NN) method. The Euclidean norm is used as a distance measure, but the estimate is rejected if

$$|\bar{y}_j - \bar{a}_{ij}| \leq 2\bar{\sigma}_{ij} \quad (6)$$

where  $CP_i$  is the “nearest” calibration point.

- b. Quick response (QR) system: this serves to ease the creation of ubiquitous learning materials, and also ease outdoor learning activities, for additional features of the context aware u-learning environments. This is incorporated into touch screen mobile devices.

Some set of activities are needed to create a context-aware model to sequence learners’ activity. The context-aware model adopts the use of Felder and Silverman Learning Style Model

(FSLSM) to automatically detect learning style. FSLSM categorises a learning styles based on five dimensions: active&reflective dimension, sensing&intuitive dimension, sequential&global dimension, inductive&deductive dimension, and visual&verbal dimension [9]. To obtain the degree at the learners belong to a specific dimension in the FSLSM model, the system analyses the learners profile and learners; style using fuzzy cognitive map (FCM).

FCM consists of nodes represented by concepts  $C_i$  and interconnections strength  $e_{ij}$  between concept  $C_i$  and concept  $C_j$  [20]. It is a collection of concepts and there are cause and effect relationship between them. Interconnections strength value  $e_{ij}$  among concepts is characterized by a weight  $w_{ji}$ . The weight is the grade of causality between two concepts. Weights take fuzzy values in the interval  $[-1, 1]$ . The sign of the weight indicates positive causality, then  $w_{ji} > 0$  between concept  $C_i$  and concept  $C_j$ , that is, an increase of the value of concept  $C_i$  causes an increase in the value of concept  $C_j$  and similarly a decrease of the value of concept  $C_i$  causes decrease in the value of concept  $C_j$ . When there is negative causality between two concepts, then  $w_{ji} < 0$ ; the increase in the first concept means the decrease in the value of the second concept and vice-versa [3]. FCM is mathematically denoted as follows [20]:

At the step  $n$ , the value  $R^n(C_i)$  of the concept  $C_i$  is determined by the relation

$$R^{n+1}(C_i) = f\left(\sum_{j=1, j \neq i}^k w_{ji} R^n(C_j)\right) \quad (7)$$

where  $R^{n+1}(C_i)$  is the value of the concept  $C_i$  at the discrete time step  $n$  and increment by 1. To reflect the overall strength of impact of an attribute on all the others, it is derived using equation (8);

$$R^{n+1}(C_i) = f\left(k_1 \sum_{j=1, j \neq i}^k w_{ji} R^n(C_j) + k_2 R^n(C_i)\right) \quad (8)$$

The coefficient  $k_1$  defines the concept’s dependence of its interconnected concepts, while the coefficient  $k_2$  represents the proportion of contribution of the previous value of the concept in the computation of the new value. Function  $f$  is a predefined threshold function. Generally two kinds are used in the FCM framework:  $f(x) = \tanh(x)$  is used for the transformation of the content of the function in the interval  $[-1,1]$  and unipolar sigmoid can be used to ensure values of concepts between 0 and 1. The function is given by:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \quad (9)$$

- c. Effective collaboration: Ubiquitous learning requires formation of group based on heterogeneity. The definition of learners’ features is used to compare the groups numerical attributes which is based on results from FSLSM and FCM.

A student learning style,  $L_i$ , is represented by a 5-tuple,  $L_i(T_1, T_2, T_3, T_4, T_5)$  which corresponds to the values for the five dimensions used in the Felder Silverman Learning Style Model (FSLSM) where  $-11 \leq T_i \leq 11$ .

Based on the context, individual learner can be represented by the projection of the vector on any of the five dimensions. For heterogeneous groups, it is important that the learners consider different values of the attributes. Distance between two learners

$L_j$  and  $L_k$ : the similarity of two learners is evaluated through the distance between the vectors representing the learners. Applying the Euclidean distance, this becomes:

$$d(S_j, S_k) = \sqrt{\sum_{i=1}^n (T_i(L_j) - T_i(L_k))^2} \quad (10)$$

where  $T_i(L_j)$  represents the value for a particular attribute  $T_i$  for a student  $L_j$  and  $n$  represents the number of attributes. In this research work, the attributes to be considered include *group\_work*, *attitude*, *subject\_interest*, *achievement\_motivation*, *study\_level*, *collaboration\_level*, *performance\_level in the subject*.

Arithmetical mean (AD) computed from learners' distances is represented is equation (11):

$$AD = \frac{\sum_{j=1}^{m-1} \sum_{k=j+1}^m \sqrt{\sum_{i=1}^n (T_i(L_j) - T_i(L_k))^2}}{\frac{m(m-1)}{2}} \quad (11)$$

where  $m$  is the number of learners and  $n$  is the number of tuples.

The group average distance (GA) is represented in equation (12):

$$GA(L_1, \dots, L_m) = \frac{\sum_{j=1}^{m-1} \sum_{k=j+1}^m \sqrt{\sum_{i=1}^n (T_i(L_j) - T_i(L_k))^2}}{\frac{m(m-1)}{2}} \quad (12)$$

where  $m$  is the size of each group and  $n$  the number of tuples.

The Internal Euclidean distance is represented in equation (13):

$$IE(L_1, \dots, L_m) = \frac{\sum_{j=1}^{m-1} \sum_{k=j+1}^m \sqrt{\sum_{i=1}^n (T_i(L_j) - T_i(L_k))^2}}{\frac{m(m-1)}{2}} \quad (13)$$

Based on this technique, the heterogeneous group formation amongst effective engaging learners would have been established based on learners activities within the learning processes..

### 3.3 The AES Diagram

Figure 2 is the UML activity diagram showing the sequence of typical activities the learner is involved in while using the system.

Figure 3 is the UML Class diagram showing the classes (objects) that make the AES software system. The class diagram gives a more detailed description of the system, illustrating the components of the system and the communications there in.

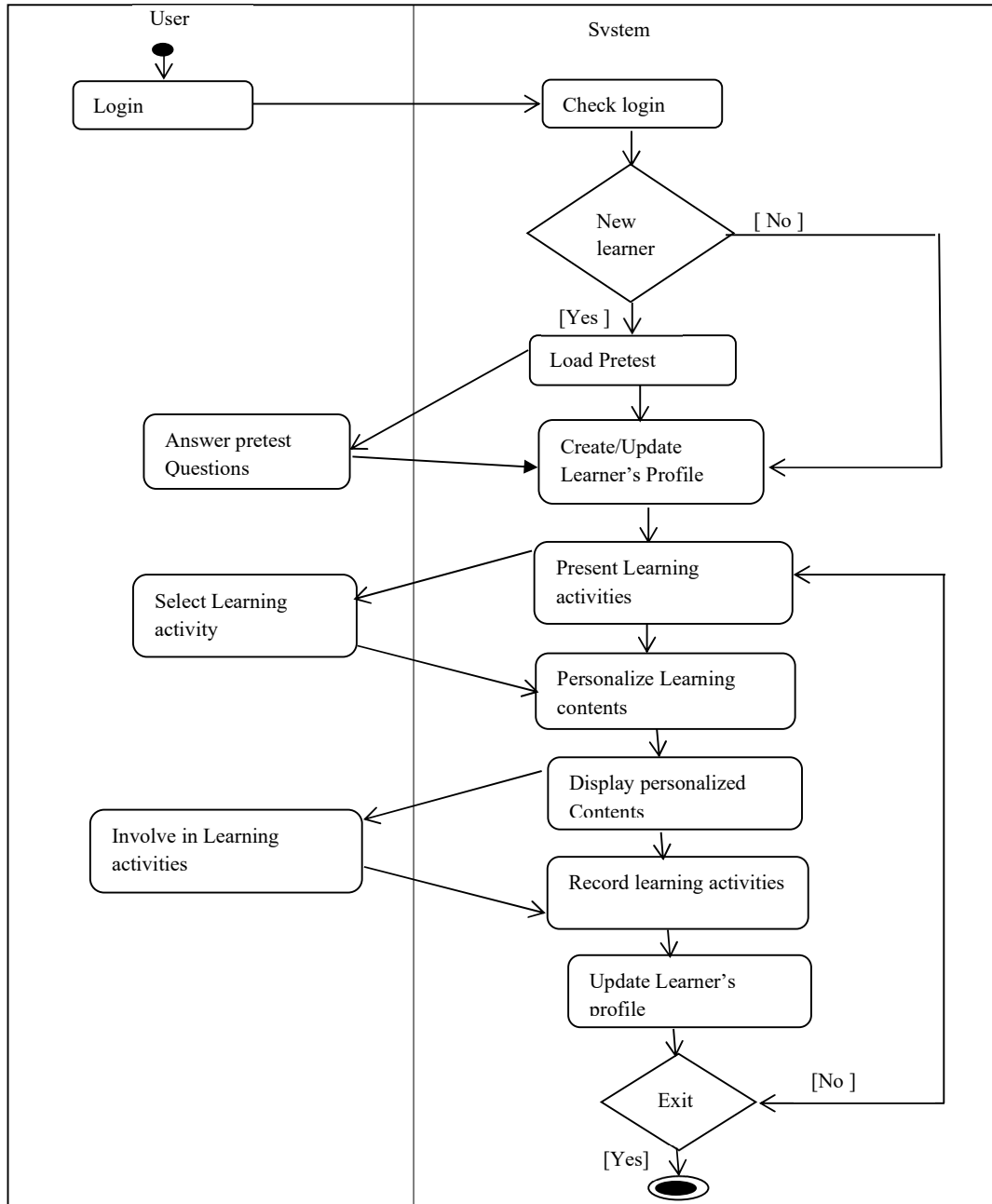


Figure 2: Activity diagram of the AES



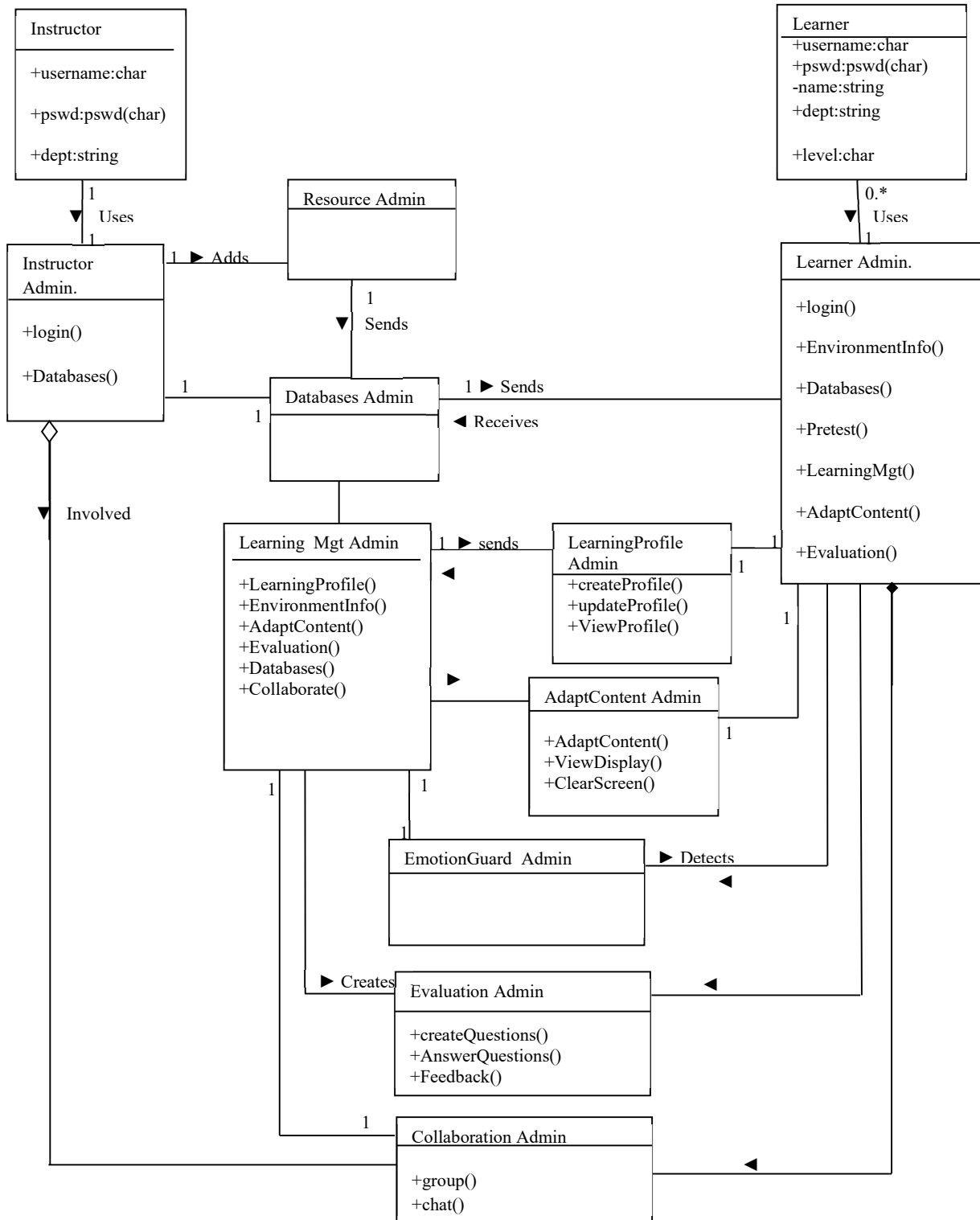


Figure 3: Class Diagram of the AES

### 3.4 Discussion: Result and Analysis

The research study employed a survey to gather feedback from students regarding the impact of the adaptive eLearning system on their learning performance. The survey contains 10

questions, which address students' experiences with the Adaptive eLearning System. These questions can be further broken down into two subcategories, as five questions address personal records of the students and 5 address application-student communications. The second subcategory has the

following questions: Application improved communication with lecturer/facilitator; Application improved communication with the system administrator; Information prompted conversation with an administrator; Access to Application prompted conversation with Lecturers; Student-Application Communication improved learning performance

Table 1: Survey Questions Frequencies

Survey Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Application improved communication with lecturer/facilitator	0	0	0	11(26%)	31(74%)
Application improved communication with the system administrator	0	0	3(7%)	9(21%)	30(72%)
Information prompted conversation with an administrator	0	0	2(5%)	13(31%)	27(64%)
Access to Application prompted conversation with Lecturers	0	0	4(9%)	13(31%)	25(60%)
Student-Application Communication improved learning performance	0	0	3(7%)	11(26%)	28(67%)

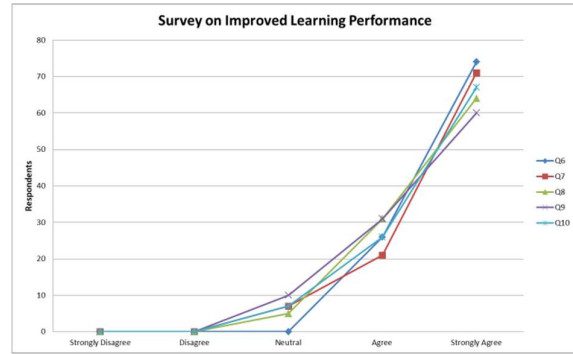


Figure 4: Survey on improved learning performance

Table 2: Descriptive Statistics of the survey questions

Survey Question	N	Mean	Median	Standard Deviation
Application improved communication with lecturer/facilitator	42	4.738	5	0.445
Application improved communication with the system administrator	42	4.642	5	0.618
Information prompted conversation with an administrator	42	4.595	5	0.586
Access to Application prompted conversation with Lecturers	42	4.5	5	0.672
Student-Application Communication improved learning performance	42	4.595	5	0.627

Table 1 and Figure 4 show that all 42 respondents are either neutral (7%), or agree (21%) or strongly agree (72%) that the application has improved their communication with the system administrator. A total of 100% of the respondents reported that they agree (24%) or strongly agree (76%) that the application improved communication with their lecturer/facilitator, while 0% disagreed that the application improved communication with their lecturer/facilitator. When ask if the application has improved their conversation with their lecturers, a total of 91% of agreed or strongly agreed with the statement while only 9% remained neutral to the question.

When asked if the communication within the application has improved learning performance of the learners, a total of 93% of respondents agreed (26%) or strongly agreed (67%) with the question while only 7% remained neutral to the question.

### Assessment Performance

The research also used an experimental method where students are divided into two separate groups (Group A and Group B). The students are selected from a population of 110 students in their second year of learning. The experimental group (Group B) is made up of 42 students while the control group (Group A) is made up of 30 students. The same assessment where given to both groups but the experimental group made use of the adaptive eLearning System, while the control group was taught based on the traditional face-to-face method.

Both groups were administered an administered a pretest which helps establish a baseline measurement of student performance and allows for a comparison of the two groups' initial abilities. The data collected include test scores and grades. The posttest record of both groups shows as shown in Figure 5 represents the outcome of the students' performance. The satisfactory label is assigned to learners who achieve a performance index between 50% and 70%, whereas the distinction label is given to learners who attain a performance index of 70% and above. Group B outperformed Group A, with a larger proportion of learners achieving higher scores. Approximately 85% of learners in Group B exceeded the satisfactory threshold, while only 47% of learners in Group A managed to surpass the same threshold.

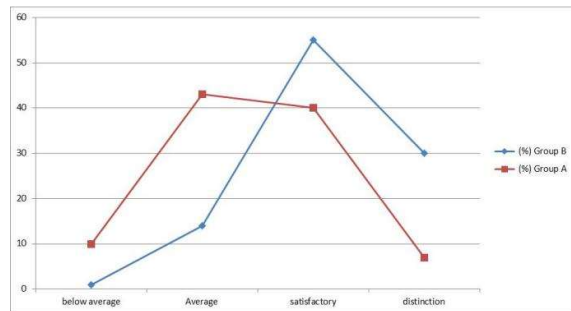


Figure 5: Assessment Performance

## 4. CONCLUSION

The research work presents a model and design of an Adaptive E-Learning System (AES) that is aware of learner's location, support synchronous and asynchronous learning process, generate learning path and execute effective collaboration based on context-aware activity sequencing in accordance with learners profile. The model presented provide necessary tools and framework for adaptive online learning system developers. The architecture of the system consists of key components: Learner Interface (AES portal, including Pre-test sub module), Learner Profile module, Learning Activities Management Module (collaboration, evaluation, offline services, etc.), Adaptation Module, Learning Content Analyzer Module and Database Module, all interconnected for effective communication of data among components.

The main functionality proposed in this system is the determination of learners' activities especially on learning resources using Ant colony clustering algorithm, application of Felder-Silverman Learning Style Model (FSLSM) to categorise a learner's learning styles and use of Fuzzy cognitive map (FCM) to obtain the degree at which learners belong to any of FSLSM category.

The conceptual framework diagram, activity diagram and class diagram created using standard software engineering tools, provide a generic framework with description that will aid developers interested in creative adaptive e-learning system to meet the ever increasing need of such systems in the online educational enterprise. Further implementation of the system is currently ongoing using real life cases.

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