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Towards a Personalized Adaptive Remedial e-Learning Model

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Abstract: Recently, demand for database programming specialists has greatly increased in Kenya. These professionals play a key role in the computing and software development industries. Although database programming skills are key fundamentals for learners in computing disciplines, skills mastery by students is still not easy. For these reasons, this study establishes an adaptive remedial learning model to assist learners in their quest of gaining skills online. The proposed solution adopts the use of fuzzy logic theory to create an appropriate learning path based on the learners' prior concepts miscomprehensions. This technique selects a suitable remedial materials for learners after constructing a learning path based on the learners' preference. After evaluation of the model through conducting several experiments, it is proposed that it can be used to offer a comprehensive and stable remedial learning environment for any LMS. Analysis of the model by learners confirm that it has achieved the effects of remedial and adaptive learning.

Keywords: Adaptive Learning, Remedial Learning, Fuzzy Logic, Concepts miscomprehension.

1. Introduction

Skills in database programming are key for any students in computer science, engineering and related disciplines [1]. Additionally, these skills are prerequisite for learners majoring in the disciplines of natural sciences, mathematics, and engineering [1]. Works found in [2] as cited in [1] notes that general programming skills are necessary for the development of computer expertise. Although programming is a major fundamental subject for students in computer science and engineering related disciplines, learning to master database programming is not a walk in the park. A study by Winslow [3] as cited in [1] observed that, it can take a minimum of a decade of training and experience for a novice to become a well-versed programmer. Current practices show that database programming skills are taught primarily via a teacher-centred approach [1] limiting the ability of trainers being able to identify problems faced by individual trainees. Furthermore, trainees gradually tend to lose interest in learning if they cannot solve problems instantly while in the learning process. This calls for innovative ways of training learners to solve their own problems in learning a database programming platform.

Increasingly, enhancing the learning performance and satisfaction of students is becoming the key driver in educational systems. In this regard, tutors strive to accurately conduct evaluations of varying students' competencies which can naturally differ in terms of level of knowledge, interest, social background, and level of motivation [4-5]. This requires tailoring of the training process to adapt to each learner's needs and preferences.

As much as expert teachers in a classroom could be aware of the differentiation in characteristics and abilities of learners, limits exist as to the degree of adjustments of the learning environment by the trainer to optimally take care of each student [4]. However, it has been shown that use of smaller groups of students can facilitate the accuracy of learning and analysis of these learning characteristics and abilities [4]. Studies has shown that one-to-one teaching have higher chances of yielding higher learning performance [6-8] something impractical in traditional classroom setups.

The internet has vividly become a central ecosystem for learning environment experienced by students, facilitating ubiquitous learning [9]. Academic institutions in both developed and developing economies are continuously adopting e-learning platforms as a result of upward surge in providers [10]. As quoted from works in [11], "*E-learning can be viewed as a system of electronic learning whereby instructions are devised or formatted to support learning and then delivered to the intended beneficiaries through digital devices that normally come in the form of computers or mobile devices*".

There exist two approaches for designing e-learning platforms. One approach is in the form of an instructor-led also referred to as synchronous. The second format entails individual study which is self-paced, known as asynchronous e-learning [11]. Learners have the opportunity to determine the time and place of learning in asynchronous e-learning [11-12]. The pace at which they want to undertake their study also solely depends on them.

Synchronous e-learning, is real-time instructor-led training [11, 13]. In this approach, learning time is scheduled when students log on. Instructors are available online and students are required to establish communications directly with the instructors [13]. Unfortunately, it seems that the challenges faced in normal classrooms stemming from lack of interactions also bedevils both asynchronous and synchronous e-learning environments. It therefore means that the diagnosing process cannot be fully applied between the teachers and students. In addition, one-size-fits-all approach is adopted in the design of the e-learning courses. This mode does not consider the individual students' unique needs and abilities [14, 15].

Recently, adaptive e-learning systems have gained prominence. The main objectives of these systems is to monitor the learner characteristics and styles, adjust and deliver appropriate instructional materials to support and improve the learning process [16, 17]. These systems are able to deliver instructional content by continuously adapting [1] to the individual learner needs and requirements [16, 18]. In order that adaptive learning systems becomes efficient, it is largely dependent on methodology employed for information collection and diagnostic as regards to learner needs and characteristics as well as how the information is processed for developing adaptive learning and intelligent learning context [16]. Classification of learner needs and characteristics can be based on their current knowledge, learning styles, affective states, personality traits and learner goals [14]. These factors are considered mainly because they help learners achieve their learning goals and objectives [19]. Personalized learning course content can be delivered to learners [16]. This can be in form of feedback from trainers, sequencing of content and presentation of contents in different teaching style approaches [16].

1.1 The Problem

In as much as there exist many studies suggesting the benefits of developing an adaptive e-learning system to aid the learning process, the existing systems still have challenges for learners, including inability for learners to take control of the process and use of too much effort to go through the process, which can be referred to as cognitive overload [20-22].

Ability of a learner to control their learning: Each learner should be able to study online independently void of instructors at any place and at any time. Unfortunately, students with little or no prerequisite knowledge may not be able to comprehend some of the course content due to their difficulty. This becomes a hindrance to learning for these category of students because research work in [20] has noted that prior knowledge is the most important factor for determining the achievements of learners. Effectively, lack of sufficient prior knowledge by learners hampers proper comprehension of the necessary concepts that could be needed for them to learn to enhance their learning performance [23].

Cognitive Overload: Keywords-based search engines tools like Yahoo and Google are popular in aiding learners seeking knowledge in online platforms. Although learners are able to easily get whatever information or course content they need, some of the materials are not organized in the form the learners would want them to be. Learners have to spend some time organizing and / or filtering these information in addition to reading them. It is noted in [24] that the abundance of online information resource could result in anxiety on the part of individual learners. Considering these facts, it becomes an important undertaking for systems to be able to offer the most appropriate learning materials directly to each learner. Available e-Learning platforms adopted by African universities are one-size-fits-all versions. There is need to make them adaptive to individual learner's needs.

This work proposes an Adaptive Remedial Learning Model (ARLM) that employs fuzzy logic theory [25] to determine an appropriate learning path based on the learners' concepts miscomprehensions. The model adapts to the learner the most suitable learning materials from an LMS according to their preferences. This in turn, facilitates more efficient remedial learning.

2. The Model Architecture

In this section, an approach for automatic construction of suitable learning path that appropriately determines suitable remedial materials from an LMS according to the learners' preferences is presented.

2.1 Model Modules Description

Figure 1 shows the proposed model architecture. It has four modules which include, *Learner-Testing*, *Inference*, *Learner-Style-Determinant* and *Learner-Path-Determinant*.

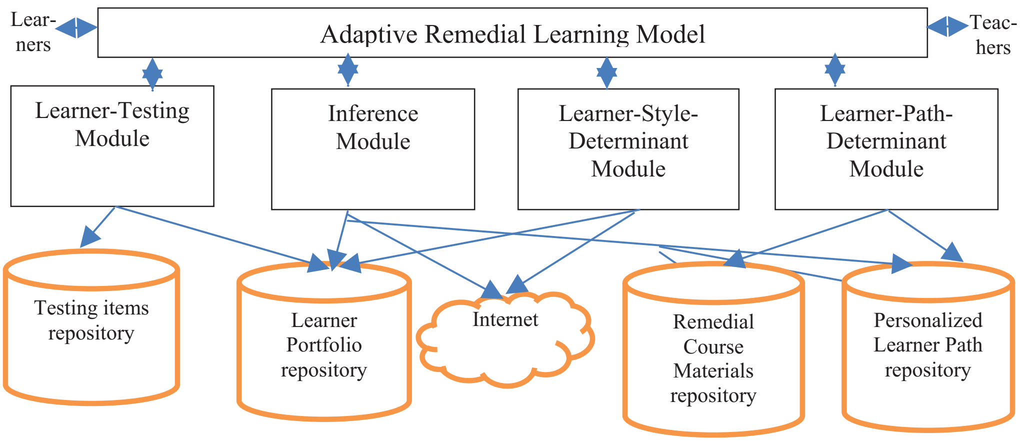

Figure 1: Adaptive Remedial Learning Model (ARLM) Architecture

First, the model allows teachers to design and create questionnaires for determining learning style. It is also proposed that learners can respond to the forty four (44), two answer questions in the Soloman and Felder's Index of Learning Styles Questionnaire [26] to determine their learning style. Trainers are can also edit testing items in the testing items repository. Secondly, after creation of testing items, a learner can then log into the system for learning and testing purposes. If the learner is a novice, he or she should first analyse his or her own learning style through the learning style questionnaire provided by the model or provided in [26]. At the end of the entire testing process, the model analyses the examination results of each learner to identify the concepts they miscomprehended. These analysis results are then stored in the learner portfolio repository. Fuzzy logic theory is used in the *Inference Module* to infer a learning path that is appropriate for each learner depending on how they miscomprehended concepts which is based on the learning material accessed from the LMS. Learning style determinant module retrieves the appropriate remedial course content from the LMS based on the generated learning path. The retrieved material should satisfy the learners' preferences and the information is stored in the remedial materials repository. Learner path determinant module determines the most suitable paths for each learner. For each course unit, the module also determines the most suitable learning materials. All these are based on the learners' concepts miscomprehensions and their preferences. In general, using the model, efficient learning for all the learners is facilitated. The following section describes the modules of this model.

Learner-Testing module: Two roles played by this module have been described above.

Inference module: Using fuzzy logic technique enables systems to emulate the process of human reasoning especially when making decisions based on imprecise information that is available [27]. In this study, inference module helps in constructing suitable learning paths that are based on learner's testing results. While identifying appropriate learning paths based on the learners' miscomprehension of concepts, it is of utmost importance for the model to put into consideration the degree of relationship of two different concepts [1]. High degree of relation between the concepts should lead to the concepts being provided to the learner in succession. In this work, the fuzzy inference mechanism establishes the degree of the relationships between each concept pair among other candidate concept units in the following stages, 1) *Input*, 2) *Fuzzification*, 3) *Inference* and 4) *Defuzzification* [28].

Stage 1: Input

In this phase, Input Linguistic Features are formed. For each concept pair, feature values' computation is done so that they can be processed in phase two of the technique. For this study, feature values include, 1) Extension of *Concepts* (E*C*), 2) Similarity of *Concepts* (S*C*) and 3) Coherence of *Concepts* (*CC*) as suggested in [29].

Extension of Concepts: This feature value relates to one of the basic ideas in text mining domain where two terms appearing together frequently in a text are perceived to have high chances of being correlated or connected. In this study, if learning materials with Concept *C1* subject matter frequently references Concept *C2* subject matter, it implies that C1 and C2 are correlated and that *C1* could be a prerequisite of *C2*. This could be the reason because researchers believe that learning of any type should progress gradually. Furthermore, the concepts that frequently appears in the learning process could be the ones which have already been learned. To effect this, the study has adopted a probability model for the simple reason of exploring the correlation between the two concepts in a voluminous materials in an online LMS.

***Similarity of Concepts*:** This feature value relates to closeness of or similarity between given concepts i.e. concept C2 in question to concept C1 that already has been accessed by the learner. In this case a very high value, presumes that the learner is already familiar with the concept, and it follows that the learner finds it easy to comprehend it. It therefore means that if a concept correlates highly to another one that has already been comprehended by the learner, it should more likely be availed to the learner. To effect this, the study proposes use of a cosine measure for computing similarity weighting for each concepts pair. Computation of the similarity of each concept pair, has been achieved by aggregating the weightings of each candidate concept pair.

Coherence of Concepts: In order for the learner to successfully understand the subject matter with ease, the continuity in the contents of the concepts is key. This should be a driving force when the model constructs the sequence of learning material (learning objects) to be provided to the learner. This study proposes automatic construction of suitable learning paths. These learning paths should be having related concepts to enhance content continuity and achieve already identified coherences between them. Finally, coherence weightings from the generated concept lattice derived in [30] are summed up for individual candidate concept.

Stage 2: Fuzzification

In this phase, the linguistic feature values concept pair (*i.e. EC, SC, CC defined in stage 1)* degree of membership is calculated. For each linguistic term, the triangular membership function has been used. As a result, for each fuzzy input variable, this work has defined three linguistic terms, thus, *Lower*, *Middle*, and *Upper.* A specific function is defined for each term to represent its degree of membership.

Stage 3: Inference

In this phase, AND and OR operations are used which employs a total of 27 rules. The rules are based on various combinations of the linguistic terms (three in number) and the fuzzy input variables (also three in number). Prior knowledge from domain experts have been used to define all the fuzzy inference rules. For each rule, an output variable is defined denoted as *DCR,* which means the *Degree of Concept Relationship.* These output take the following forms of associated linguistic terms, *DCR-Lower*, *DCR-Middle* and *DCR-Upper.* There are three final values of the output variable *DCR* between two different concept units. The learner should receive the candidate concept unit with the highest value.

Stage 4: Defuzzification

Defuzzification takes place in this phase using the discrete center of area (COA) method as the computation method. To demonstrate the inference module process, assume that a concept a learner has miscomprehended is the "Select * from" in the Oracle database platform. Identification of two candidate concepts "Select * from" and "create table" is done using Apriori algorithm [30]. Phase one then computes the three feature values, *EC*, *SC* and *CC*, respectively. In phase two, the linguistic feature values degree of membership are calculated. As an example, suppose two candidate concepts "Select * from" and "Create table" have degrees of membership of the linguistic terms lower, middle, and upper for the three fuzzy variables in the following manner: {(0, 0.41, 0.59), (0.31, 0.69, 0), (0, 0.54, 0.46)}, as shown in Table 1.

Table 1: Linguistic Terms Fuzzy Variable Degree of Membership

		Linguistic terms		
		Lower	Middle	Upper
Fuzzy Variables	EC	0	0.41	0.59
	SC	0.31	0.69	0
	CC	0	0.54	0.46

For illustration purposes, suppose eight related rules are created. The *Us* in the last column of the left box in Figure 2 are the degrees of membership of the rules' linguistic term *DCR*s. For each rule, the *AND* operation takes the minimum value of the degrees of membership of fuzzy variables. The output of this operation is in the last column of section A in Figure 2. From the results of the AND operation, the *OR* operation takes the output with maximum value. This is shown in Figure 2 as the value farthest to the right after section B. The output of this step is the final result of *DCR_U* of *DCR*, which is 0.55. This process is repeated to compute the final values of other linguistic terms. At the end of the process, *defuzzification* of the relationship degree of each concept pair is carried out. An example of an outcome of this phase is shown in Table 2.

Table 2. An Example of Degree of Relationship Matrix for a Concept Pair

	Select * From	Create Table
Select * from		0.66
Create table	0.11	

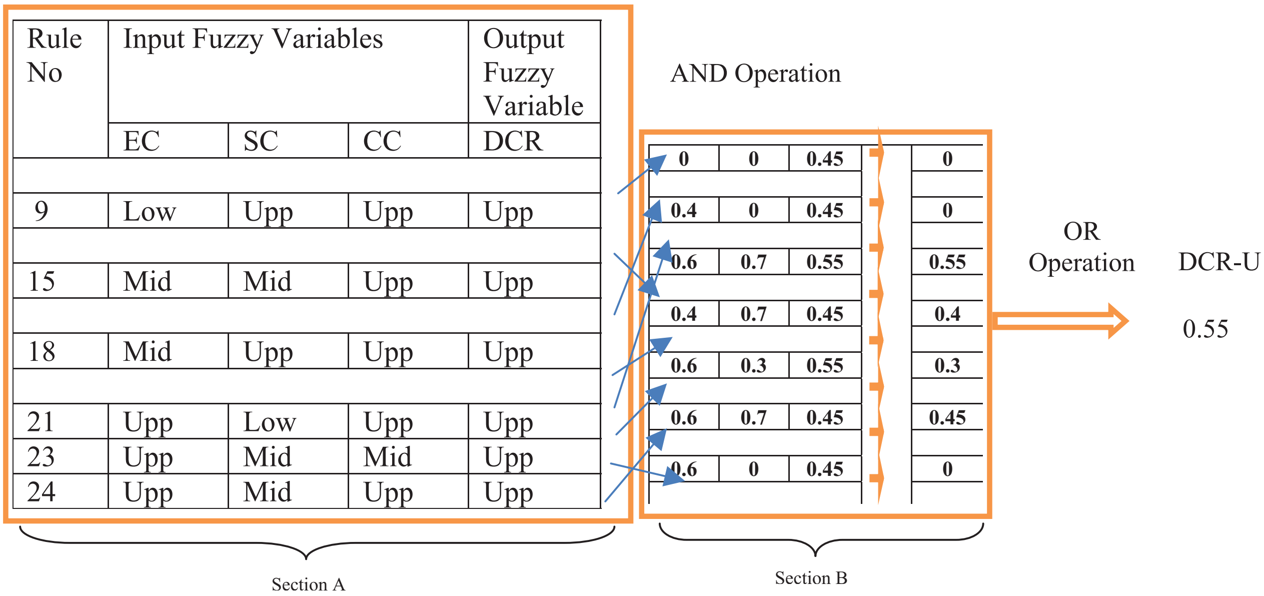

Figure 2: Calculation of Fuzzy Rule Inference

Learning path determinant: During learning process after concept miscomprehension, learners should be provided with remedial learning resources to facilitate better understanding of the terminology that was initially misunderstood. For the concept to be well learnt, prerequisite knowledge of the relevant terminology is required. In this case, preparation of some of the information associated to the prerequisite knowledge should be done for such a learning activity. Depending on the necessity, these prior knowledge concepts must be presented at the initial stages of constructing a learning path. In this study *DCR* matrix presented in [1] is used to construct suitable learning paths for each learner. Meanwhile, to construct a suitable learning path to continuously address the learner's concepts miscomprehensions, choosing of the main learning subject is done after taking into consideration the concept unit that most closely matches the concepts miscomprehension. The candidate concept for the prerequisite knowledge becomes the one with the highest weight of relationship to the concepts miscomprehension. The same process is followed for other units which are found and arranged subsequently according to their relationship weights.

3. Experimentation Results

3.1 Design of the Experiment

In this study, experiments were conducted to evaluate the effectiveness of the proposed model. To achieve this, 55 undergraduate (second year of study) students from the Computer Science department of Dedan Kimathi University of Technology, Kenya, were involved in the experiments over a semester (May-August, 2018). The experiment took fourteen (14) weeks, three (3) hours each week in a computer laboratory. The students comprised of 9 females and 46 males. Database programming skills are key for all students undertaking Computer Science and engineering related courses. Database programming is required for the course. Oracle database programming platform was used as an example. Additionally, it was noted that a majority of the participants did not have prior database programming knowledge before the learning started.

The study adopted a randomized pre-test–post-test control group design. The key aspects of the experiments were to determine the effectiveness of the model. Assignment of all participants to the either experimental or control group were purely random. The control group which had twenty eight (N =28) used the model void of the recommended learning paths and adaptive learning materials. The experimental group with membership of twenty seven (N=27) used the recommended learning paths and adaptive learning materials for remedial learning. Trainers designed the testing sheets for both the pre-test and post-test sessions. The sheets composed of multiple-choice questions. It was decided to differentiate the pre-test items from the post-test items. To determine reliability and validity of the evaluation measurements, four Oracle database programming platform experts were involved. Learners were randomly grouped and pre-testing done. Afterwards, the learners were engaged in remedial learning processes for four (4) months. The performance of learners in both groups was measured. To self-evaluate their learning performance after the four months of the experimental process, the learners who participated were then asked to take a post-test.

3.2 Results of the Experiment

In this section, evaluation results based on learners' performance are presented. After participants had finished the pre-test, it was necessary to verify the differences between experimental and control groups using an independent sample test. The results of this process are shown in Table 3 with the average scores on the pre-test for both groups.

Table 3. The Pre-Test Evaluation Results

	Group Category	N	Mean	Std. Dev.	Std. Err. Mean
Pre-test	Experimental	27	55.931	11.689	2.250
	Control	28	55.892	10.890	2.059

According to the results of the analysis in Table 4, it can be observed that between the two groups (experimental and control) there were no significant differences in pre-test results (t = .011, *p = 0.991 > .05).

Table 4. The t-test of the pre-test of learning performance

	Levene's Test for Equality of Variances		t-test for Equality of Means					95% CI of the Difference	
Equal variances assumed	0.097	0.756	0.011	53	0.991	0.033	3.045	-6.074	6.140
Equal variances not assumed			0.011	52.395	0.991*	0.033	3.049	-6.084	6.150

*p > .05 (CI: 95%)

It shows the closeness in abilities of both groups in database programming. After remedial learning of four months and so that a determination could be made in regard to whether both groups, displayed any significant statistical differences in their performance, the paired samples t-test was used on the post-test. After the learning process and as shown in Table 5 and Figure 3, results of the difference in the mean (pre-test and post-test) scores show no significant improvement in learners' abilities for the control group (t = 0.657, **p = 0.517 > 0.05). The same results show a remarkable improvements for the experimental group (t = -2.550, *p =0 .017 <0.05). It is observed that there was significant improvements for the participants in the experimental group in comparison to those in the control group.

Table 5. Paired Samples t-test of the Pre-Test and Post-Test for Experimental Group and Control Group.

Pair		Paired Difference							
		Mean	Std. Dev.	Std. Error Mean	95% CI of the Difference				
EG (N = 27)	Pre-test and Post-test	-6.667	13.587	2.615	-12.042	-1.292	-2.550	26	0.017*
CG (N = 28)	Pre-test and Post-test	1.964	15.831	2.992	-4.174	8.103	0.657	27	0.517**

*p < .05 (CI: 95%) EG-Experimental Group
**p > .05 (CI: 95%) CG-Control Group

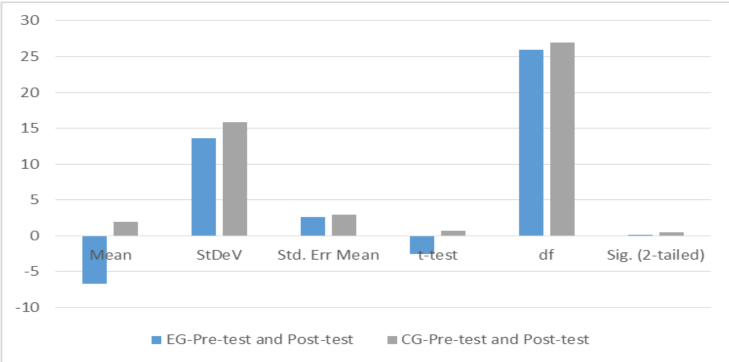

Figure 3. Paired Sample t-test of EG and CG Pre- and Post-Tests

During the experimentation, researchers explored the possibility of the model being more helpful while in use by a certain type of learners (considering low-achievers and high-achievers). To determine this, the category of students used in the experiment was split into two. This was done as per the results from their pre-test scores (learners with grades below thresh-hold and those with grades above thresh-hold).

From the experiment results, it is shown that low-achiever learners had made a lot of progress (t = -5.133, p = 0.000 < 0.05) as shown in Table 6. This was in contrast to high-achiever learners which from the same results, it is shown that they did not make significant improvement in their database programming abilities (t = 1.242, p = .236 > 0.05) as shown in Table 7.

Table 6: EG Low Achievers Paired Samples t-test of the Pre-Test and Post-Test.

Pair		Paired Difference							
		Mean	Std. Dev.	Std. Err. Mean	95% CI of the Difference				
Learners who scored low grades in the EG (N = 13)	Pre-test and Post-test	-16.538	11.616	3.222	-23.558	-9.519	-5.133	12	0.000*

*p < 0.05 (CI: 95%) EG: experimental group

Table 7: EG High Achievers Paired Samples t-test of the pre-test and post-test

Pair		Paired Difference							
		Mean	Std. Dev.	Std. Error Mean	95% Confidence Interval of the Difference				
Learners who scored high grades in the EG (N = 14)	Pre-test and Post-test	2.500	7.532	2.013	-1.849	6.849	1.242	13	0.236*

*p > 0.05 (CI: 95%) EG: experimental group

4. Conclusion

Automatic search of relevant remedial database programming course materials according to learners' preference has been possible through the model proposed in this study. It is the opinion of researchers, backed by works in [1] that solutions that provide guidelines and adaptation of course materials are necessary. They help learners improve their learning ability and for this study the database programming skills. Learners are in a position to control their learning process. The systems are also able to organize these course materials in an online environment and thus improve the effectiveness of learning activities. Inference from the experimental results leads to the following conclusions: From the pre-test results comparison, there was no significant difference between the experimental group and the control group. To be specific, before the experiment both groups displayed similarity in terms of skills for database programming. After using the model, learning effectiveness was raised for the learners in the experimental group whose results showed that they had registered a remarkable progress in their database programming ability. Furthermore, low-achieving students who researchers believe had significant database programming skills set deficiency and therefore needed to learn at a slow pace progressively with proper guidance, showed great improvement. This was evident when given a learning path, they were able to significantly progress to greater extent.

As relates to some of the contributions to theory and practice of this study, it is common knowledge that many learning materials in existing learning settings, are compiled and edited manually which are both expensive in cost and human resource. The model proposed in this work can facilitate the analysis of the learner characteristics and obtain online learning materials automatically from any LMS. The model adaptively provide learners with suitable learning materials based on the appropriate learning path. Results of the post-test survey reveals increase in the learners' interest in database programming. This was evident when they displayed greater interest in the learning materials provided by the model. Finally, this model provide suitable learning path for access to remedial materials to learners who then engage in progressive remedial learning at all times. Therefore, researchers in this study believe that these research results form a base through which other research works can be done as a follow up of such studies in the future.

The model is developed for use in institutions of higher learning in Africa. The final output of this project will be open source hence it will be freely available online for use by any learning institution for learning and / or research and further development. Lack of wide internet infrastructure coverage to allow learning off campus can hamper its success. For anyone who want to implement a similar project, it is advisable to seek collaborations with stakeholders for greater acceptance and deployment. The next project phase include further development and hosting of the model in git-hub for free access to other users.

5. Implementation

The proposed model is dependent on internet availability which is not a problem in Kenya. Kenya's broadband market has been transformed by a combination of increased investments in network upgrades among the key providers as well as by the landing of four fibre-optic submarine cables. A number of ISPs have become second-tier telcos by rolling out national and metropolitan fibre backbones and wireless broadband access networks. A number of major WiMAX deployments and Fibre-to-the-Premises (FttP) rollouts have been undertaken, which have pushed fast broadband connectivity to a greater number of subscribers in urban areas. Nevertheless, the vast majority of broadband subscribers are on mobile networks. Mobile network operators are concentrating investments on LTE, so enabling customers to take up a range of high-end data services and applications. It is necessary to develop a mobile based model to be used by majority of learners who own mobile electronic devices. This will be done in the next phase of the project.

According to 2011 estimates, about 13.5% of the African population has Internet access. While Africa accounts for 15.0% of the world's population, only 6.2% of the

World's Internet subscribers are Africans. Africans who have access to broadband connections are estimated to be in percentage of 1% or lower. Africa is progressing towards greater connectivity, prices are falling slightly and internet use is increasing. Nonetheless, there are still some obstacles to expand access to mobile internet, such as affordability and investment in network coverage expansion.

The current version of this model requires further testing in different setups to test its reliability and resilience. Authors will implement the model at their university and seek collaborations with other research institutions to scale it up so that other learning institutions can adopt the technology.

The model is deployed in institutions of higher learning and facilitates learning in English. It is assumed that students in these institutions have basic knowledge of English language. For that reason, the probability that the analysis of learning styles after the learners have responded to the proposed questionnaire is high. However, for non-English speaking learners, the probability of correct learning style analysis is low, unless some translation is made to the language they understand.

The adoption of e-learning platforms is already taking place. However, not much is happening on adaptive learning systems. The same platforms hosting e-learning systems can embrace adaptive versions. Once proper internet infrastructure is in place, a dedicated division of e-learning platforms and courses should be created. All academic divisions in the learning institutions can be encouraged to offer some of their courses in the platform. Continuous monitoring and assessment should be carried out to ensure quality and effectiveness of adaptive remedial e-learning.

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