

A Model of Adaptive Assessment for Mobile Learning in an Open and Distance Education University of Pakistan

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ABSTRACT

The use of technology has become inevitable in every field of life including the education. The distance learning is also shaping towards smart online learning, therefore, posing many challenges of content development and delivery through the smart devices. One of the challenges is the development of adaptive assessment for anytime and anywhere mobile learning. The COVID-19 has posed an extra requirement of reshaping pedagogies on hand-held devices. The current study takes up these challenges and proposes a model of adaptive assessment for mobile learning. The Item Response Theory has been employed to estimate the learning ability and tailor a personalized learning trajectory. The model was implemented on a bachelor level course offered by an open university of Pakistan. A mobile application was developed and one hundred and eighteen students were enrolled. They used the app in addition to other traditional activities for a duration of one semester. The result of final examination of adaptive batch was compared with the previous same course offered through the traditional distant learning mode. The result showed sizeable improvement in the knowledge level of the distant learners. This research opens up an avenue of anywhere and anytime learning through the use of smart devices. It can help policymakers, educationists and technologists to align their online learning practices during the current pandemic.

Keywords: E-assessment, Adaptive system, Mobile learning, e-learning, Distance education

1. INTRODUCTION

Distance Education (DE) is a non-traditional system of education which is independent of distance and time [1]. It gives greater autonomy to the learners by providing anywhere anytime learning opportunities [2]. It also facilitates teacher to deliver rich contents without their spatial and temporal presence. Due to flexible approach, the DE mode is growing rapidly and traditional institutes are also converting their programs into modern DE environment [3]. The recent advances got more attention due to its potential of remote access & services through the use of technology and thus the paradigm of e-learning or online learning has been introduced [4]. The latest development has led a new paradigm of mobile learning which is an advanced form of e-learning.

Mobile learning also known as m-learning is the use of mobile devices for education and training. It is the delivery of academic activities through PDAs, pocket PCs and mobile phones [5]. Learning through different settings, social and material associations by utilizing individual electronic gadgets is also a form of m-learning. It is conceivable to learn at point and place of your choice, until you have a cutting-edge smart device associated with the Internet [6]. The proliferation of smart devices in education has introduced a wide range of mobile-based instructional methods, including mobile-based learning and assessment. In the context of bring-your-own-devices (BYOD) policies, mobile devices can be used alternatively to desktop computers for conducting electronic assessment [7].

The mobile-based assessment can be conducted anytime and anywhere, thus offers extended capabilities such as personalization, context-awareness and ubiquity [7]. However, the introduction of mobile-based assessment in education is developing very slowly due to barriers of technical infrastructure, non-availability of personalized contents, professional development, and organizational policies [8]. Another critical factor is its adaptation for different type of users. One of the opportunities is the increased smartphone use during COVID-19 [9]. However, mobile users are very fast interactors and they keep on switching the contents very rapidly which do not match with their requirement or personality. Keeping in view these challenges this paper focuses on the design and development of a model for an adaptive assessment in a distant learning environment.

2. LITERATURE REVIEW

The phenomena of DE have grown with the evolution of technology and different generations have been reported [1]. The first generation is based on written or printed materials in the form of manuals and books delivered through the postal correspondence. Most of the open universities of the world started their distance education with the first generation. The second generation uses the broadcast media such as radio and television transmissions in addition to the print media. These approaches were time bound and therefore not flexible for anywhere and

anytime learning. The continuous evolution of technology leads towards the third generation, where two-way communication was introduced via audio and video conferencing. However, the World Wide Web (WWW) and Internet technologies set new directions towards effective e-learning or online learning and the fourth generation was introduced with the blend of interactive multimedia. The delivery through smart devices is also a part of it which ensures portability and speed through mobile learning. The fifth generation is the development of adaptive and intelligent learning systems which is an open area of research in today's mobile learning. Mobile Learning offers compelling opportunities for open and distance learning. The mobile devices are available to majority of the world population i.e. more than three billion users around the world including both developed and developing countries [10]. Students can effectively use mobile devices for browsing academic contents and playing multimedia lectures. It can be used for spontaneous and context aware mode of learning. The portability adds extra advantage of carrying the device with every step or movement of the user [11]. The device is also private as every user can restrict the access of his/her device to unauthorized persons. They can participate in collaborative as well as individual activities of learning with complete control over the touch screen-based user interface. The important components of m-learning are student, teacher, digital content and assessment [12]. Digital contents are small learning objects that can be played and re-played over the devices. Assessment is an important component that can be used to assess the knowledge level of students over a span of learning activities. The research on mobile learning has been divided into many areas that range from technology to pedagogy. The technology acceptance of m-learning is one of the major areas addressed by the researchers [13] which have been conducted to evaluate the perception of potential users on the paradigm shift. Another area is the design of frameworks where the focus is on the development of m-learning solutions for particular domains [14]. One more area is the success of m-learning and learner's intentions [15]. Some of the studies have also focused on the context-aware learning for an individual or group of learners [16]. However, the assessment through m-learning is still an open area of research which needs to be addressed.

The revolution in technology has changed the dimension of instructional and assessment materials. Therefore, the traditional assessment strategies are transforming towards the electronic assessment which is the use of information technology for the knowledge evaluation [17]. Adaptive assessment is a dynamic form of testing; that adjusts itself depending on the response of the student [18]. It is also called Computerized Adaptive Testing (CAT) which selects the appropriate questions to adapt the learning and assessment needs. There are five components of CAT i.e. question databank, initialization step, question presentation algorithm, scoring and termination criteria [19]. The question databank comprises of assessment objects with varying difficulty level. These are mapped with the instructional objects and are calibrated for each topic and subtopics. The initialization step is the starting point where the very first tutorial is presented followed by the assessment quiz. After initialization, the assessment algorithm determines the current knowledge and loads the appropriate level of instructional objects. The algorithm iteratively works to present and re-present the contents and tailors a personalized learning path. The termination criteria is checked with each iteration to update the knowledge level. The development of CAT requires psychometric capability of the learning algorithm as reported in the literature review [20]. Adaptive assessment is an active area of research in the field of mobile learning. Some authors termed it as an evolutionary development in the field of e-learning that supports anywhere and anytime learning with mobility and personalization [21]. These studies have addressed many dimensions of learning & assessment through mobile and computer systems. One aspect is the development of technology systems and platforms that can be customized with diverse difficulty levels of content for each individual examinee. They provide access to a huge variety of digital contents and provide vast opportunities for assessment and learning. The type of assessment is also an area of concern which has been discussed in the purview of both summative and formative assessments. There is an opportunity to address the device contextualization with adaptivity features in a localized scenario [22, 23]. Therefore, the current research has undertaken these challenges to propose a model of adaptive assessment for ODL learners. The IRT has been reckoned as one of the best techniques for the psychometric measurement of the learner activities [24]. It illustrates how individuals communicate with test objects by mapping the properties of items on an instrument, the individuals who respond to these items, and the measurement of the underlying trait. The main components of IRT are Item Response Function (IRF), Location and Discrimination. IRF relates the latent feature to the likelihood of an object being endorsed, whose position is determined by the Location and steepness is calculated by the Discrimination. These components drive the item selection, ability estimation and stopping rules.

3. PROPOSED ADAPTIVE E-ASSESSMENT MODEL

To address the research challenges found in literature survey, and extending a previous work [25], we are proposing a model of adaptive assessment to personalize the learning methodology through m-learning. The model has three core components i.e. domain module, student module and adaptive engine, as shown in Figure 1.

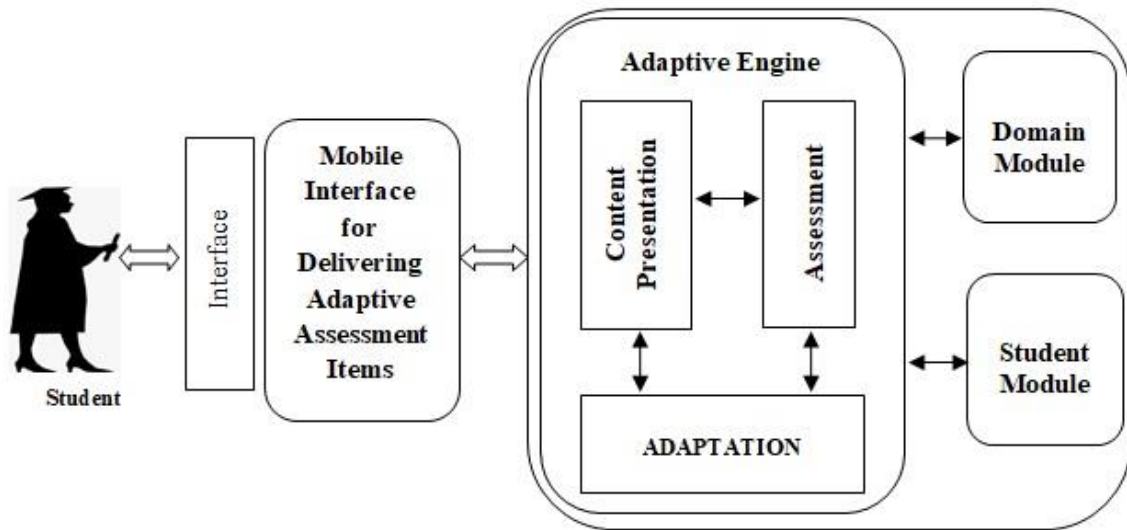


Figure 1. Proposed Adaptive Assessment Model for Mobile Learning

3.1 Domain Module

Domain module is composed of knowledge components of the subject matter. It first manages the course hierarchy in the form of units (chapters) and each unit is comprised of topics and sub-topics. The level of granularity in terms of content depth and breadth represents a coherent concept of knowledge with measurable knowledge outcomes as shown in Figure 2. The second aspect is the format of learning contents which has been adopted and customized [26] as a combination of multimedia objects to match with the learning styles of the students.

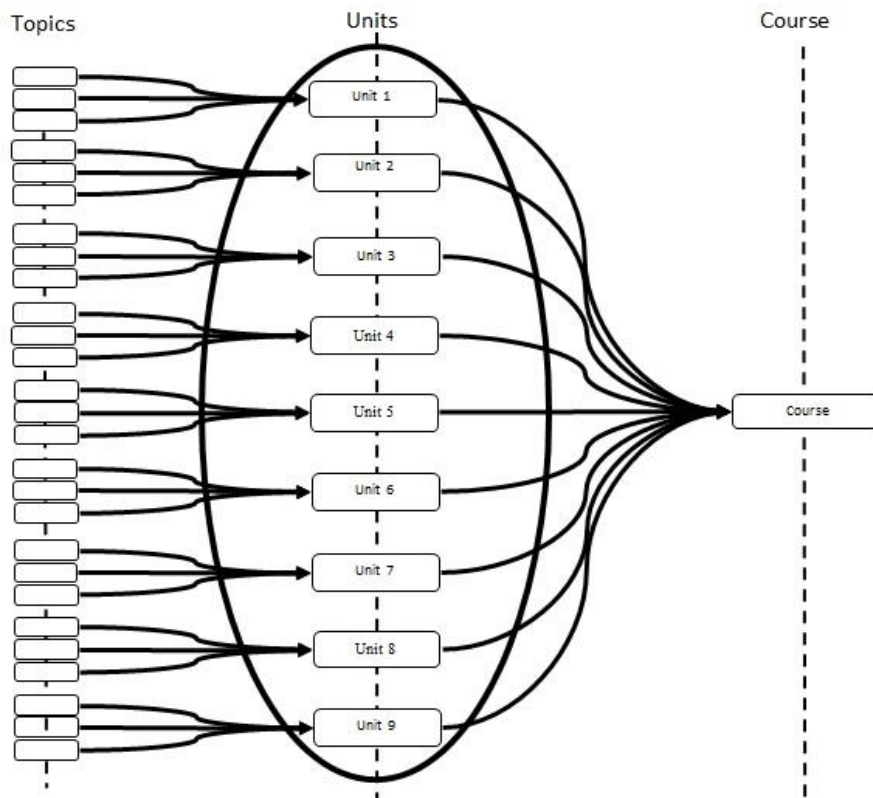


Figure 2. View of the Granularity Level

The difficulty level is also defined to construct a personalized learning path for individual students as shown in Figure 3. Beginner level covers the basic concept of topics in a unit. The moderate level elaborates more detail and advance level focuses on expert knowledge of the unit. The assessment objects are associated with each difficulty level of the unit and are developed by the subject expert. The sub-components of assessment objects are defined to execute the learning algorithm. The brief description is shown in table 1 and working methodology is defined in adaptive engine module (Section 3.3).

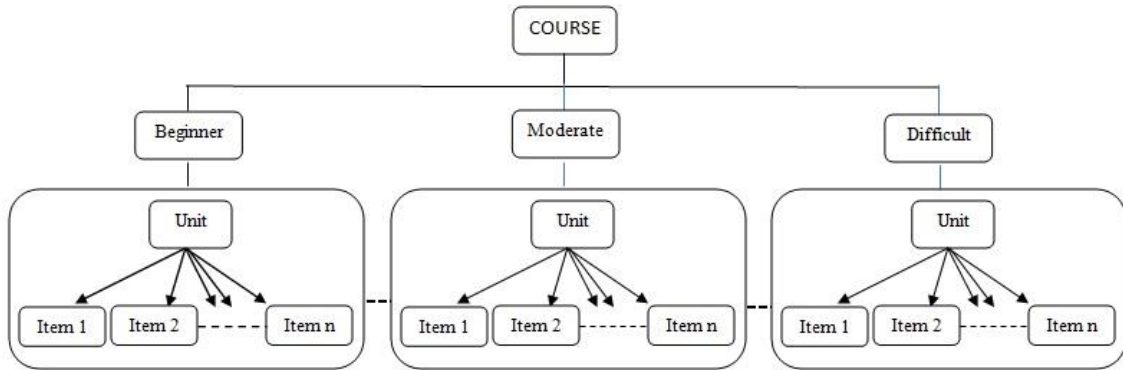


Figure 3. Difficulty Level for Contents

Table 1. Sub Components of Assessment Module

	Sub Components	Description
1	Item	A question in the assessment test.
2	Initial Item	The very first question presented to the learner.
3	Ability Estimation	It is the estimation of knowledge level of learner after attempting the assessment item.
4	Response	It is answer to a question.
5	Evaluate	It marks the answer as correct or incorrect.
6	Stopping-Rule / Criteria	It refers to a rule or set of rules that decides that the test/assessment must stop now.

3.2 Student Module

Student module is designed to gather static and dynamic information as shown in Figure 4. The demographics include learners' name, roll number, E-mail address and password, as entered during the registration process. This information remains the same except the password and is used to initialize the adaptation strategy. The dynamic information includes the ability estimation, knowledge level and learning path which continuously changes as per learning algorithm.

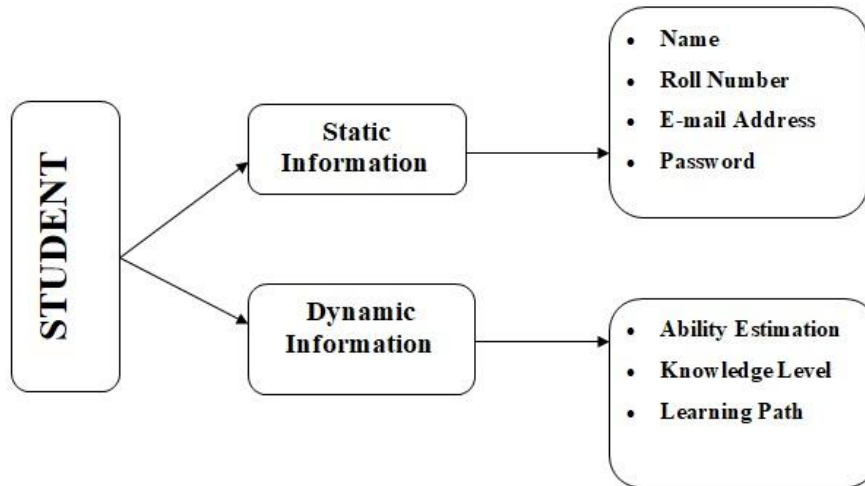


Figure 4. Data Stored in Student Module

The flow chart for initialization and updating the student model is shown in Figure 5. During initialization the student is registered in the course and assigned login credentials. During updating the students is provided with the tutorials and the assessment quizzes. The details are described in the next section.

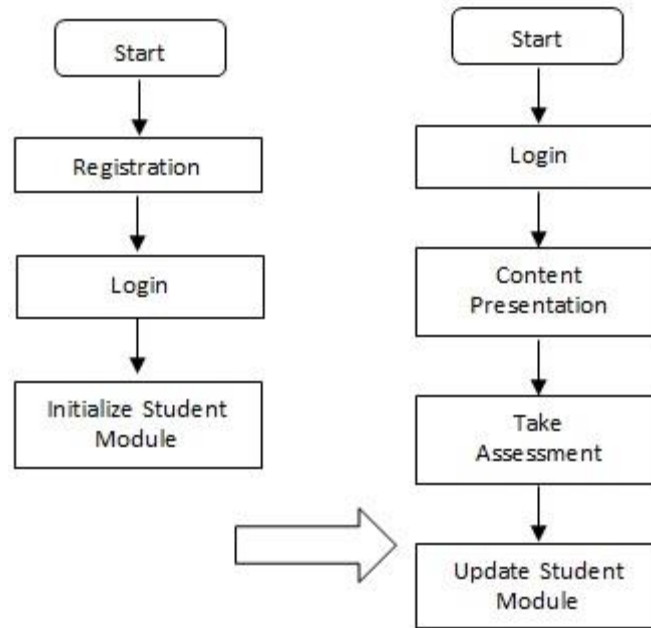


Figure 5. Flowcharts of Initialization and Updating of Student Model

3.3 Adaptive Engine Module

Adaptive engine module comprises sub-modules of content presentation and assessment. It coordinates with domain and student module as shown in Figure 6.

3.3.1. Content Presentation

The mobile user interface loads the contents from the domain module and presents it to the learner. Every unit starts with the basic tutorial that is presented in three formats as discussed in domain module. After browsing the tutorial, the learner is invited to appear in the self-learning quiz. The procedure is repeated as per learning flow as shown in the Figure 6.

3.3.2. Assessment

Assessment is the most important part in our proposed research model. The assessment objects are loaded and re-loaded during a fixed time interval. The ability of learners is estimated using the IRT. At the end of each cycle, the student model is updated with the current knowledge of the learners. The details of working parameters are as follows:

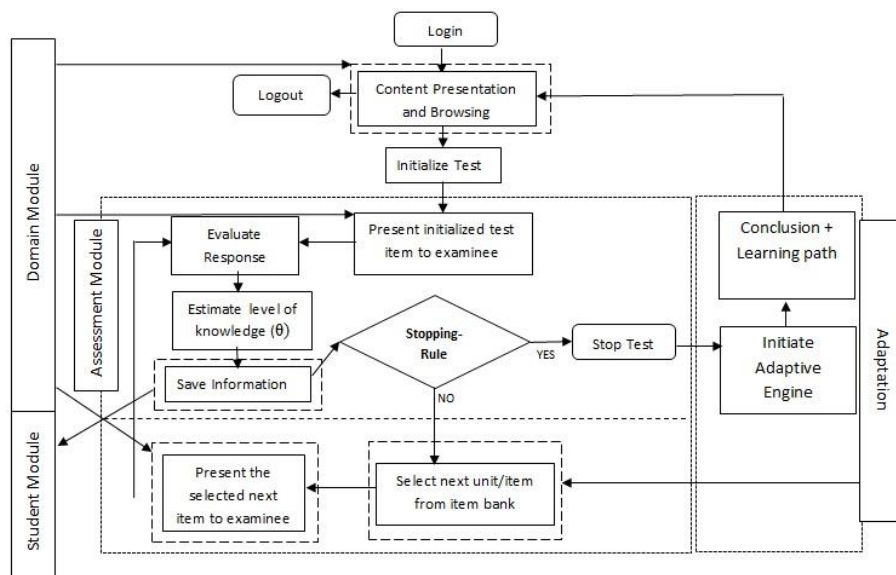


Figure 6. Assessment Module Overview & its interaction with other modules

a. Item Selection

The initial item is selected from the pool of beginner level, which is attempted by the learners. The correctness or wrongness of the answer invokes IRT to dynamically select the next item of appropriate difficulty level.

b. Ability Estimation

The ability is estimated by using the function of maximum likelihood which starts with some priori value. It is assumed that each learner has an ability scale called θ and the possibility of a correct answer is $P(\theta)$, which is calculated by using the equation 1.

$$P(\theta) = \frac{1}{1 + e^{-(\theta - b)}} \dots\dots\dots 1$$

Where: θ is ability level, b is item difficulty parameter and e is the constant.

c. Saving Information

All the results/ data generated after evaluation and estimation are saved/updated into student module. This information is then utilized by adaptation sub-module to generate learning path.

d. Stopping Rule

Stopping rule control the flow of questions and their timing as defined by the subject expert.

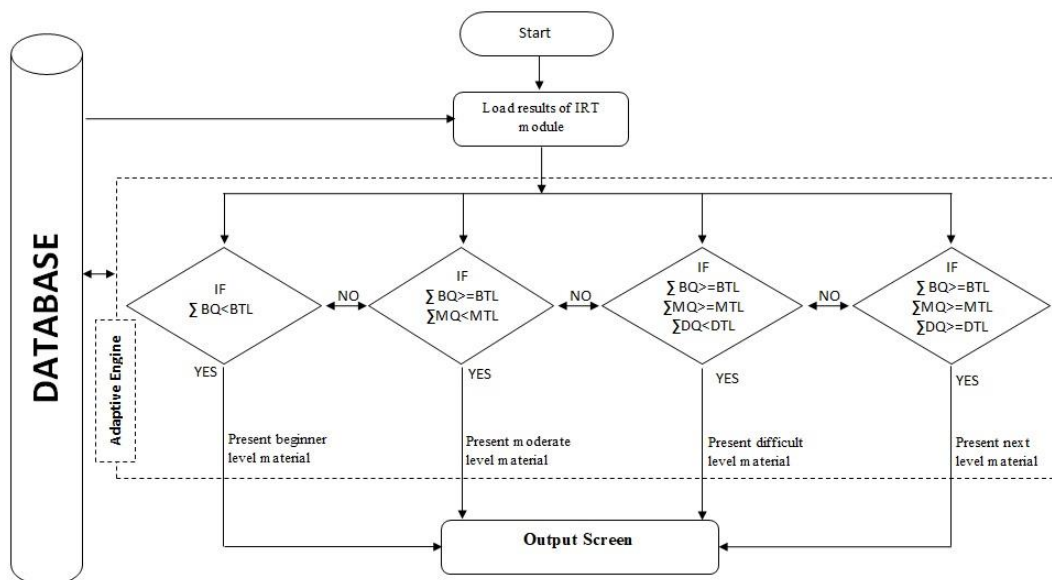


Figure 7. Adaptive Engine Flow Chart

e. Learning Path

There are three levels of learning i.e. Beginner Threshold Level (BTL), Moderate Threshold Level (MTL) and Difficult Threshold Level (DTL). The adaptive engine controls the progression and route the learner through each level of knowledge as shown in the Figure 7. The students get questions of varying difficulty as per his/her ability and the knowledge level is updated accordingly. The threshold levels of beginner, moderate and difficult as associated with the percentage are 70%, 60% and 50%, respectively.

In case, a learner fails to achieve beginner threshold level (BTL) means the sum of correct answers ($\sum$ “sum of”) of beginner level (BQ) is less than BTL, the learning path generated by the system contains the learning material from BTL. If a learner passes beginner threshold level (BTL), the learning path generated by the system contains the learning material from higher levels and the process continues up to DFT.

4. SYSTEM IMPLEMENTATION

4.1 Technology and Interface

A mobile application was developed using Xamarin framework using Microsoft Visual Studio 2017. Representational State Transfer (RESTful) web API protocol was used for communication with metadata server. Microsoft SQL Server 2008 R2 was used as backend database server to store the data. The three architecture is shown in Figure 8.

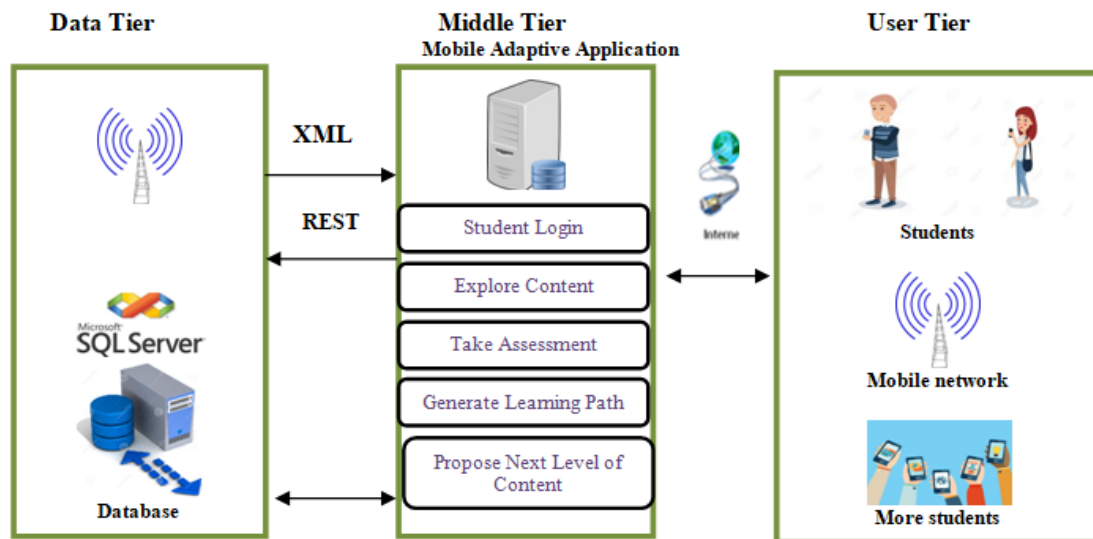


Figure 8. Three-Tier Architecture of Mobile Adaptive Assessment Application

A user-friendly interface was developed using Bootstrap version 4.0 for making it responsive and compatible with Android devices. A screenshot is shown in Figure 9. The teacher interface provided a set of commands for placing the learning objects and scheduling the online activities. The student interface was designed to engage learner for participating in online activities through their smart devices.

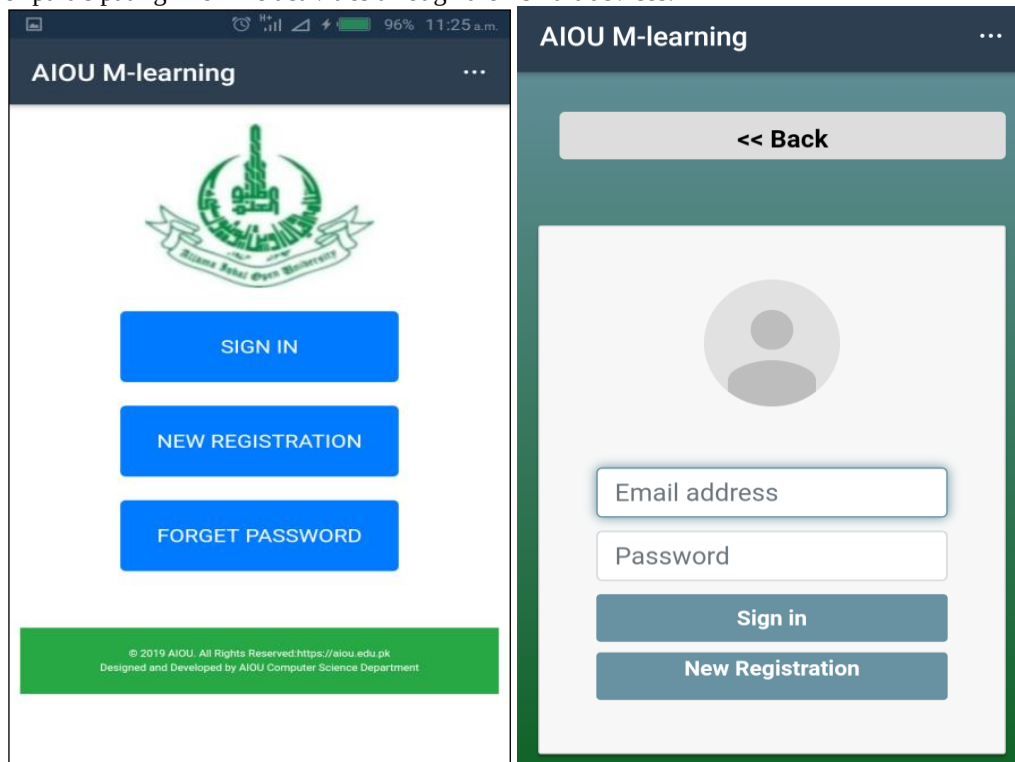


Figure 9. Login Interface

5. DATA ANALYSIS AND RESULTS

An Information Technology course of an open university was selected for the implementation of m-learning model. The number of enrolled students was one hundred and eighteen (118) who participated in the learning activities. The students browsed the contents and appeared in the self-learning quizzes and progressed through a customized learning path, created on their real time performance. The Figure 10, shows the attainment of knowledge level as a result of adaptive assessment. The 78% students were successful in achieving the expert knowledge level and only 2 %of the students left in the beginner level.

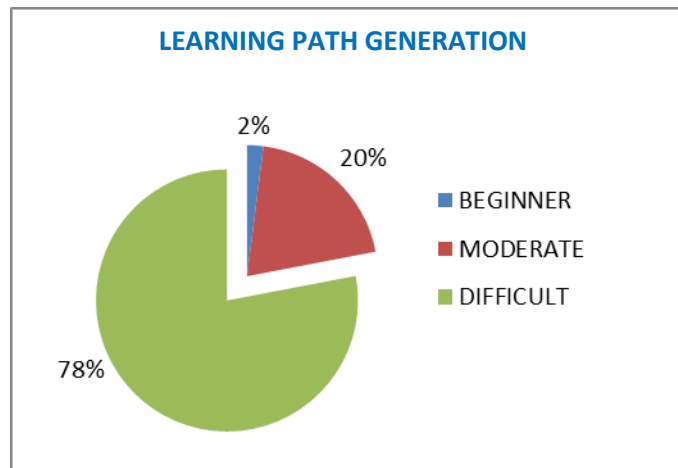


Figure 10. Adaptive Assessment Results Graph

The performance of three students is shown from Figure 11 to 13. The square boxes on the graph indicate the difficulty levels while diamonds indicate answer to each item. The diamonds on level 0 indicate incorrect answer and blue dots on level 1 indicate correct answer to each item. The line with triangles shows the ability of student throughout the assessment. The seesaw movement shows that ability of the learner rises with the correct answer and goes down as a result of incorrect answer.

The performances of best, moderate and worst students are shown from Figures 11 to 13 respectively. Red dots on the graph indicate the difficulty levels while blue dots show answer to each item. Blue dots on level 0 indicate incorrect answer and blue dots on level 1 indicate correct answer to each item. Green line which rises, or falls shows the ability of student throughout the assessment. The Figure 11 shows the ability of best learner and reveals that correct answering of difficult questions is high. While answering questions 7 to 10 the green curve tends to decline due to incorrect answers, however he/she regains the learning momentum and performance graph tends to rise for rest of the questions. The performance of moderate student is shown in Figure 12 which shows that the learner remained in the middle bound of the scale as shown by seesaw movement of green curve. This type of learner is recommended to study the next level of content to continue the studies. The analysis of low performed student is shown in Figure 13. The line is straight and remained below of the red dots showing the poor performance. All the correct answers belong to beginner level and therefore system recommends the learner to take the next level of content.

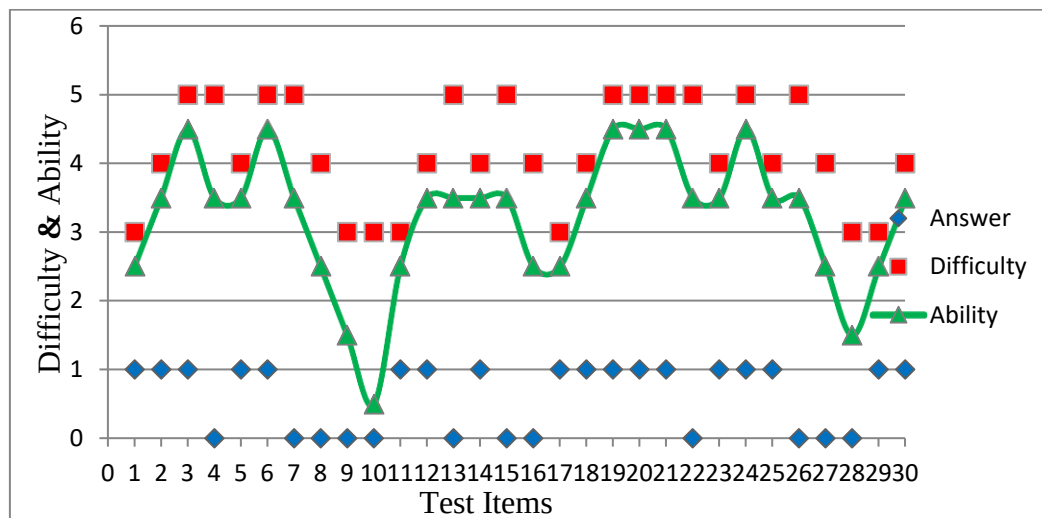


Figure 11. Progress of Student Scored Maximum

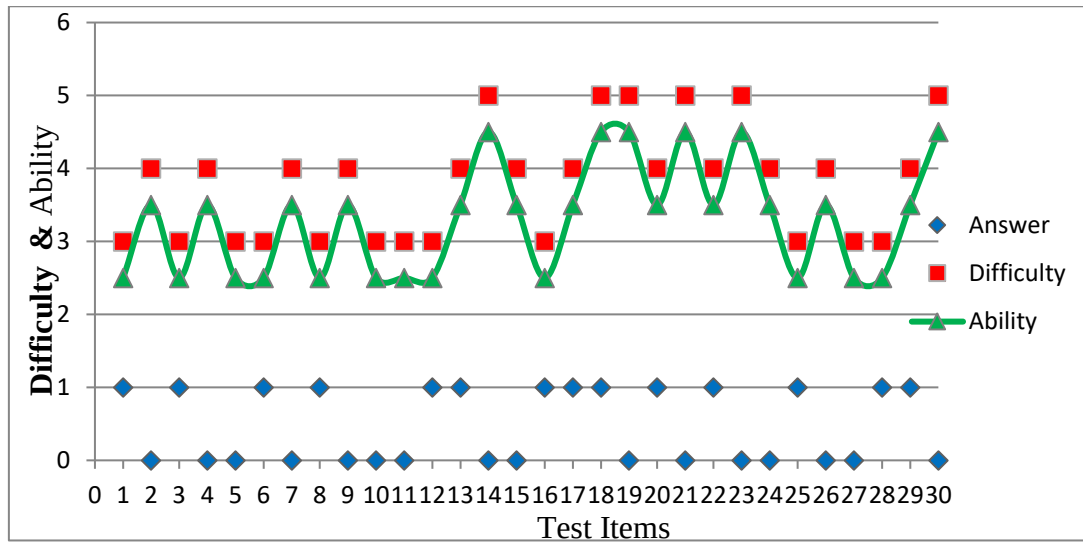


Figure 12. Progress of Student Scored Moderate

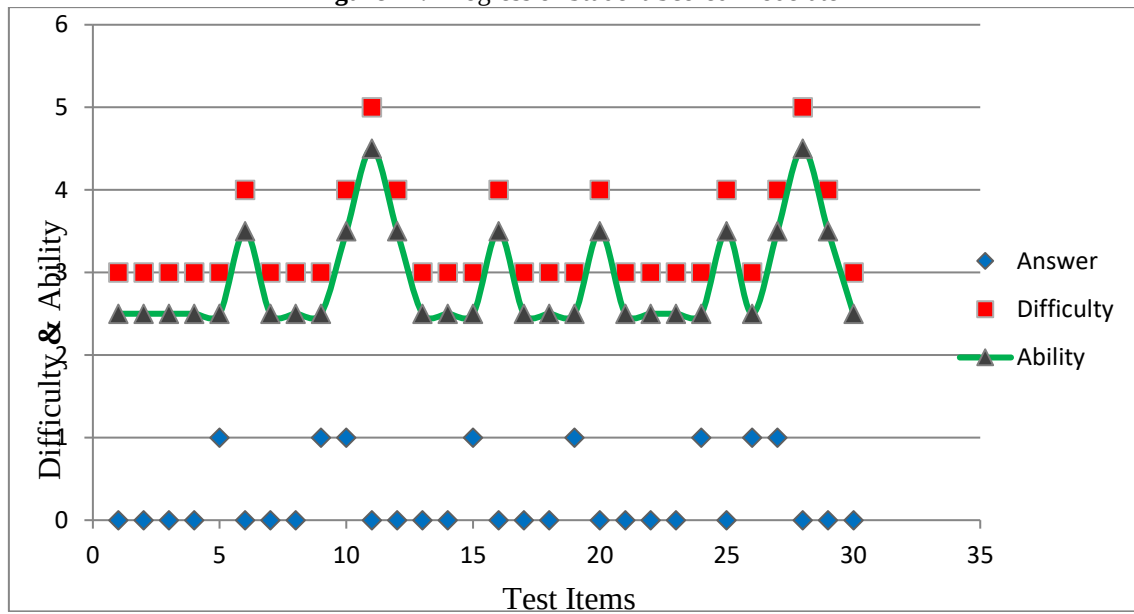


Figure13. Progress of Student Remained on Beginner Level

Another comparison of final examination result was made between adaptive assessment batch and previous batches of the same course (Group 1, Group 2, and Group 3) of the same course and the results are shown in Table 2 and Figure 14. The students of adaptive batch progressed through the semester activities with additional support of mobile app of adaptive assessment. The previous groups had already completed the semester activities through the traditional mode of distance learning. The demographics of four groups were compatible. The number of A grades of adaptive batch was higher as compared to previous batches. The number of B and C grades holders was also less in the adaptive batch.

TABLE 2. Demographics

Groups/ Demographics	Group 1		Group 2		Group 3		Adaptive Group	
Gender	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Male	52	54 %	102	66 %	91	72 %	80	68 %
Female	45	46 %	52	34 %	36	28 %	38	32 %
Total	97	100	154	100	127	100	118	100
Age Group	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
21 – 30	65	67 %	126	82 %	119	94 %	105	89 %
31 – 40	32	33 %	28	18 %	08	06 %	13	11 %

41 – 50	-	-	-	-	-	-	-	-
Total	97	100	154	100	127	100	118	100
Area	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Urban	44	45 %	89	58 %	80	63 %	87	74 %
Semi - Urban	30	31 %	42	27 %	27	21 %	18	15 %
Rural	23	24 %	23	15 %	20	16 %	13	11 %
Total	97	100	154	100	127	100	118	100

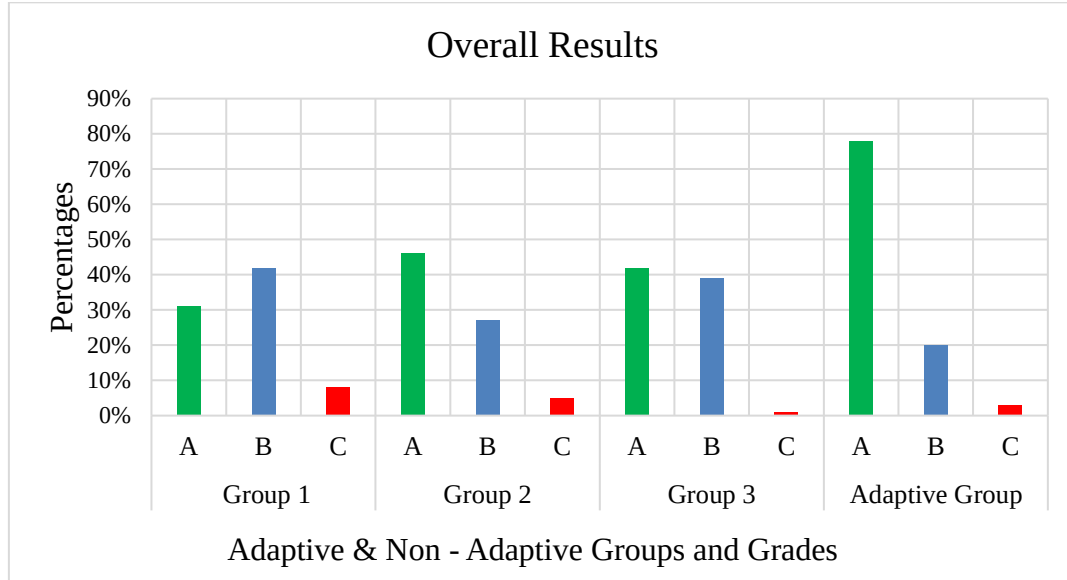


Figure 14. Comparison of Results

6. CONCLUSION

This paper has taken up the opportunity of learning through smartphones and has presented a model of adaptive assessment through m-learning. The important components of our proposed model are domain module, student module and adaptation engine. A mobile application was developed to implement the proposed model. A basic course of IT offered at an open university was selected to be offered under adaptive assessment methodology. The performance of students has been analyzed and overall comparison with the same course offered in previous semesters through traditional mode has also been made. The results shows that adaptive assessment through m-learning has helped to improve the learning of students. More courses may be prepared and offered through adaptive learning mode. This is start of a new era in educational practices and paradigm in a developing country like Pakistan.

This study provides a model of adaptive assessment through m-learning but it has few limitations. The model has been implemented on a selected course of computer science offered at an open university. Further work is required on content development to implement and validate the same model on some other courses with more diverse samples. Secondly, the prototype has been developed that could easily be executed on Android based smart devices. It may be programmed to make it interoperable for other operating systems, too.

7. DECLARATIONS

7.1 Data Availability Statement

Data was made available on request from the authors. It is not publicly available as per the policy of the institute.

7.2 Funding Statement

This research received no specific grant from any funding agency.

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