International Journal of Computer Information Systems and Industrial Management Applications.
ISSN 2150-7988 Volume 5 (2013) pp. 289-296

Improvisation of Learner's Ability using Adaptive Online Assessment Methodology

Uday Kumar Mothukuri[1], Swathi Murukutla[1], Sandesh Jain[1] and Dhanander K Jain[1]

[1] Centre for Development of Advanced Computing, India
muday@cdac.in, swathim@cdac.in, sandeshj@cdac.in, dkjain@cdac.in

***Abstract*: Learning experience can be enhanced by providing adaptability in online assessment, which is the focus of several recent research projects and papers, and with the explosive growth of information sources available on the World Wide Web. In this Paper, we present the system architecture for applying psychological methodologies to online assessment that adapts to the examinee's ability level and the other side we describe that web mining can be applied to Learning Content Management Systems to build knowledge about e-Learning and has potential to help and improve learner's performance. This paper also outlines how to increase the knowledge proficiency and skill set after identifying the ability level.**

Keywords: e-Assessment, QTI, CAT, CCT, IRT, ePortfolio, Web Mining**.**

I. Introduction

Over a long period, e-Learning has provided instructors, students and organizations with the tools to use technology for the support of learning and training. The wealth of experience gained in the classrooms or at the workplace is one side of a e-Learning coin and the assessment on the computer became the other flipside. It has become more sophisticated by providing systems to measure the performance and ability of individuals as part of the content delivery in e-Learning. Learners are increasingly more likely to experience technology based assessment directly, or to be assessed within a system that is supported by online resources.

One way for achieving all this is, by using intelligent methodologies (psychometric models) like Computerized Adaptive Testing (CAT) and Computerized Classification Testing (CCT), which improves the educative ability and experience of the learner. It is timely to review what is meant by e-Assessment, what it offers and recognize that it is more than just computerized quizzes comprising multiple choice, true or false questions. The data collected at various stages of e-Learning system is made available in ePortifolio, learner navigational patterns are logged in the server acts as the source for web mining techniques to extract useful patterns. These patterns are used to give feedback to experts for updating the course content and provide motivation to students.

The rest of this work is organized as follows. Section II describes the assessment in e-Learning. Section III is the main area that presents the system architecture and the implementation work which depicts the adaptive online assessment and also covers the potential of web mining in e-Learning. Section IV provides the result processing based on the case study and also we have covered the enhanced feedback mechanism, validity and security aspects that help in improving the quality of e-Learning system. Finally, in Section V we conclude our work

II. Assessment in e-Learning

Assessment in higher education is an ongoing process to measure cognitive abilities and improvement of student's learning. e-Learning also gives the solutions for the questions like, when we identify the weakness in a student how can we best address the problem?, How can we improve learning most effectively in a time of tight resources?, We're spending time and resources trying to achieve student's learning – Is It Working? Overall, at any level assessment allows for a continuous cycle to improve the student's performance.

e-Assessment is the use of information technology for any assessment-related activity. In general it is used to describe the use of computers within the assessment process. It can be used to access cognitive and practical abilities. Cognitive abilities are accessed using e-Testing software; practical abilities are obtained using e-Portfolios or simulation software. The two components of e-Assessment are:

1) *e-Testing* is to measure skills and knowledge by questions and assignments delivered on the computer. An e-testing system designed to focus on lower level associations comprises two components: an assessment engine and an item bank, where assessment engine is the software required to create and deliver a test. The item bank holds the questions created and the assessment engine uses the item bank to deliver the test.

2) *e-Portfolio* is used to record learner performance in the coursework and project. The use of e-portfolios in assessment has been adopted by many awarding bodies and accepted by the regulators, which enables learners to demonstrate skills.

Online Assessment is the process used to measure certain aspects of information for a set purpose where the assessment is delivered via a computer connected to a network (LAN or WAN). This online assessment identifies the initial ability level that acts as the quantitative evidence to show that some learning has occurred at student's side. Instant and detailed feedback as well as flexibility of location and time is the benefits associated with online assessments. Instructors can use assessment engine for creating questions with strict intervention, (where difficulty level, time required to attempt, objective of the question are required) that helps to find the strengths and weakness of the learner corresponding to the concept.

This form of assessment also helps to determine a baseline between formative assessment and summative assessment. Students can use these assessments multiple times to familiarize themselves with the content and format of the assessment. It can be used for online surveys, can be used by educators to collect data and feedback on student's attitudes, perceptions or other types of information that might help improve the instruction evaluations.

A. Assessment Process

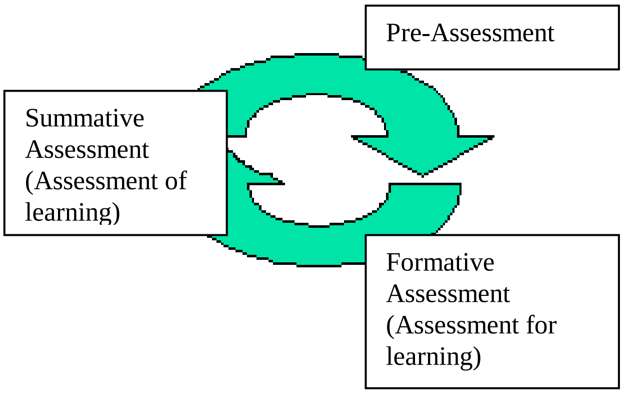

Figure1: Process (Stages) of Assessment

Fig: 1 describes the process of assessment for successful student's achievement.

1) *Pre Assessment* – This allows instructor to know what the students know before the course commencement. What is already known figures out how any individual will interact with a new learning situation.

2) *Formative Assessment* - This is used to offer feedback during the learning process. In online assessment situations, objective questions are posed, and feedback (advice or comment) is provided to the student either during or immediately after the assessment.

3) *Summative Assessment* - This type of assessment provides a quantitative grade and is often given at the end of a unit or lesson to determine that the learning objectives have been met.

B. e-Assessment Specifications

In order to create a mechanism for the sharing of high quality assessment items, global standards have emerged. The IMS Question and Test Interoperability specification (QTI) provides a common format for describing and distributing questions/items across disparate systems.

QTI [9] also enables the declarative description of many relevant dynamic features of the assessment process. For each structural constituent it is possible to attach a set of rules used to process the learner responses. Assessment is also possible to attach a set of selection and ordering rules enabling instructors to decide the sequence in which sections and items are presented to the learner and also how learner is interacting with them. QTI specifies the most common types of the scoring algorithm for result processing.

C. Computerized Adaptive Testing (CAT)

CAT is a form of computer based test that adapts to the examinee's ability level. Usage of such psychometric model allows adopting the learners ability level which helps to serve better without any supervised mechanism. This mechanism uses an iterative algorithm which presents an optimal item based on the current estimate of user's ability. The ability estimate is updated based up on the prior answers and repeated till the termination criteria are met. It has the following components

1) Calibrated Item Pool - It is the item bank which contains sets of items of various difficulty levels. These items are tuned with a psychometric model called Item Response Theory (IRT).
2) Entry Level - In CAT, items are selected based on the examinees performance. If learner's ability is known, it is fine to start from that level. Normally, CAT just assumes that the learner is of average ability, hence the first item offered being of medium difficulty.
3) Item Selection Algorithm – It estimates the learner's ability and it is able to select an item depending on the learner's attempt.
4) Scoring Procedure - If the learner answered the item correctly, the CAT will likely estimate their ability to higher grade and vice versa.
5) Termination Criterion - The termination criteria for tests like
   a) Fixed-length termination: Termination happens when the user has taken a pre-specified number of items.
   b) Standard error termination: According to this termination rule, the user continues to take test items until the learner estimate reaches a specified level of precision.

Item Response Theory (IRT) is a paradigm for the design, analysis and scoring of tests, questionnaires and similar instruments measuring abilities, attitudes or other variables. For example the e-Testing engine starts with an average ability, if the user made the correct attempt the item with higher difficulty will be administered, else a lower difficulty level item will administered. It is also the preferred methodology for selecting optimal items which are typically selected on the basis of Information rather than difficulty. It models the relationship between an examinee's cognitive level on the trait being measured by a test and the examinee's response to a test item or question. It uses the estimated scores to predict or explain items and the test performance. IRT model mathematically describes the relationship between a person's trait level and performance on an item. Item Response function is used for that mathematical description. For test items that are dichotomously scored, the item response function estimates the probability of a correct response for a given level of trait.

There are three IRT models, commonly known as one-parameter, two-parameter and three-parameter logistic models.

i. 1- Parameter model is also known as Rasch model [10]. It presents a simple relationship between the user/learner and the difficulty of items. The mathematical formula is as follows:

$$P(\Theta_i) = \frac{1}{1 + e^{-1(\theta - b_i)}} \qquad (1)$$

p_i : probability for an user/learner responding correctly
θi : ability parameter of an examinee
b_i : difficulty parameter of an item.

ii. 2- Parameter model is a generalization of the 1-parameter model. Instead of having a fixed discrimination of '1' across all the items as in 1P, 2P has its own discrimination parameter. Thus , the model is expressed as:

$$P\,(X_i = \text{correct}|\Theta) = \frac{1}{1 + e^{-a(\theta - b_i)}} \qquad (2)$$

where Θ is the student's knowledge level,
X_i : the answer (correct or incorrect) to question i,
a_i : the discrimination parameter for the question i, and
b_i : the difficulty parameter for the question i.

Here the discrimination factor describes how well an item can differentiate between examinees having abilities below the item difficulty and those having abilities above the item difficulty.

iii. 3- Parameter model uses one extra parameter called as guessing factor. One of the facts of life in testing is that examinees will get items correct by guessing. Thus, the probability of correct response includes a small component that is due to guessing. Neither of the previous models considered this guessing factor.

$$P\,(\Theta) = c + (1 - c)\frac{1}{1 + e^{-a(\theta - b)}} \qquad (3)$$

where 'c' is the guessing parameter

It is important to note that by definition, the value of 'c' does not vary as a function of the ability level. Thus, the lowest and highest ability examinees have the same probability of getting the item correct by guessing. The 1-, 2-, and 3-parameter models differ, however, in the number of parameters they allow to vary. When specifying the model to use, one should select the most stringent model that accurately represents the observed data. For example, one might choose to use the 1-parameter model instead of the 2 or 3-parameter model with multiple choice items because of a belief that the '*a*' and '*c*' parameters are inestimable or because of the small size of the data set [13]. In this paper, only the [1-parameter] rasch model is considered to identify the learner's ability and it can be extended to 2-parameter model once a complete learning cycle is completed.

D. Computerized Classification Test (CCT)

CCT is a mastery test which is similar to CAT where the items are administered one at a time and determines if the user/learner is able to be classified yet. If so the test classifies whether the student is "Pass" or "Fail". The difference between these testing methods is the termination criterion, and the scoring procedures are same in CCT but separate in CAT, because in CCT the test is terminated when a classification is made. Usage of these methodologies in assessment states that CAT effectively works for formative assessments and CCT works for summative assessments.

III. System Architecture

In this approach the Pre-Test (entrance exam) is used to identify the learnograms (pace, initial ability level, skill set) and to get quantitative evidence. The skill set includes problem solving skills, programming skills, logical reasoning skills, etc. of each learner are stored in ePortfolio, which are used to make assessment engine intelligent. These learnograms can be compared after each assessment and highlight the improvements at the learner side. The basic parameters identified at each level are mentioned in tables (refer fig-2).

Once the learner attends the main course, there are two phases of providing recommendations (guidance) and customizations for enhancing the better learning experience. The first one is during the learning phase (i) where we can identify the thinking style using the navigation patterns, learner weakness and can update or improve the content provided in the e-Learning system. Posing questions at regular intervals of time also helps to identify whether the actual learning happened or not (i.e. calculating the knowledge percentage level in the specified content).

The attributes/data collected at each phase are explained below.

1) *Knowledge percentage level:* Recording this value helps to gauge that the learner is active during the learning phase. If the user attempts the wrong answer for the question, the system prompts to go through the concept once again.

2) *Frequently visited site pages:* used to supervise the content/site pages that are very essential for a particular concept.

3) *Time slice:* is used to identify start time and end time of the learner during the learning phase.

4) *Ability level:* the ability level is rated as (-2 to 2); the difference between improved ability level and initial ability level gives the performance of each learner.

5) *Skill set:* we are considering the skill set during the pre-test, formative assessment and summative assessment to show the improved skills before and after attending the e-Learning course.

6) *Learner's Pace:* is used to find whether the user is a fast/slow learner.

7) *Lagging Area:* is identified by the learner's activities at each phase.

8) *Number of attempts:* shows the number of attempts made for each test.

9) *Motivation:* is provided based up on the all the above considered factors.

With the use of Web Mining algorithms we can predict the knowledge structure of learner, frequently visited sites (hits ratio) and learning pace. We have covered about the potential of Web mining in section III-B.

During the second phase, the actual e-Testing starts with assessment engine and the item bank. Here the instructor's role is crucial while creating the items; the additional parameters like objective of the question, difficulty level, time slice are to be entered. All these items are stored in the item bank as different sets (which act the source for IRT).

For each test a threshold value is identified for allowing the learner to move on to next learning phase (i+1). If the learner failed to get the specified threshold limit (pass mark) in certain number of attempts then the learner have to go through the same learning phase once again. If the learner or the instructor is not satisfied with the performance, retesting is also possible. The designed assessment engine is also made available to update the difficulty level of any item given by the instructor in the item bank. For example, if 60% of the users attempted a very difficult question in less time, the assessment engine will automatically reduce the difficulty level of the item using a back propagation mechanism. In this approach, tests can be designed to adapt themselves optimally for each learner; no need to waste easy items on high ability examinees, or discourage lower examinees with difficult items. By making the test more intelligent, CAT provides a wide range of benefits. A better experience for examinees, as they can only see the items which are relevant, providing an appropriate challenge.

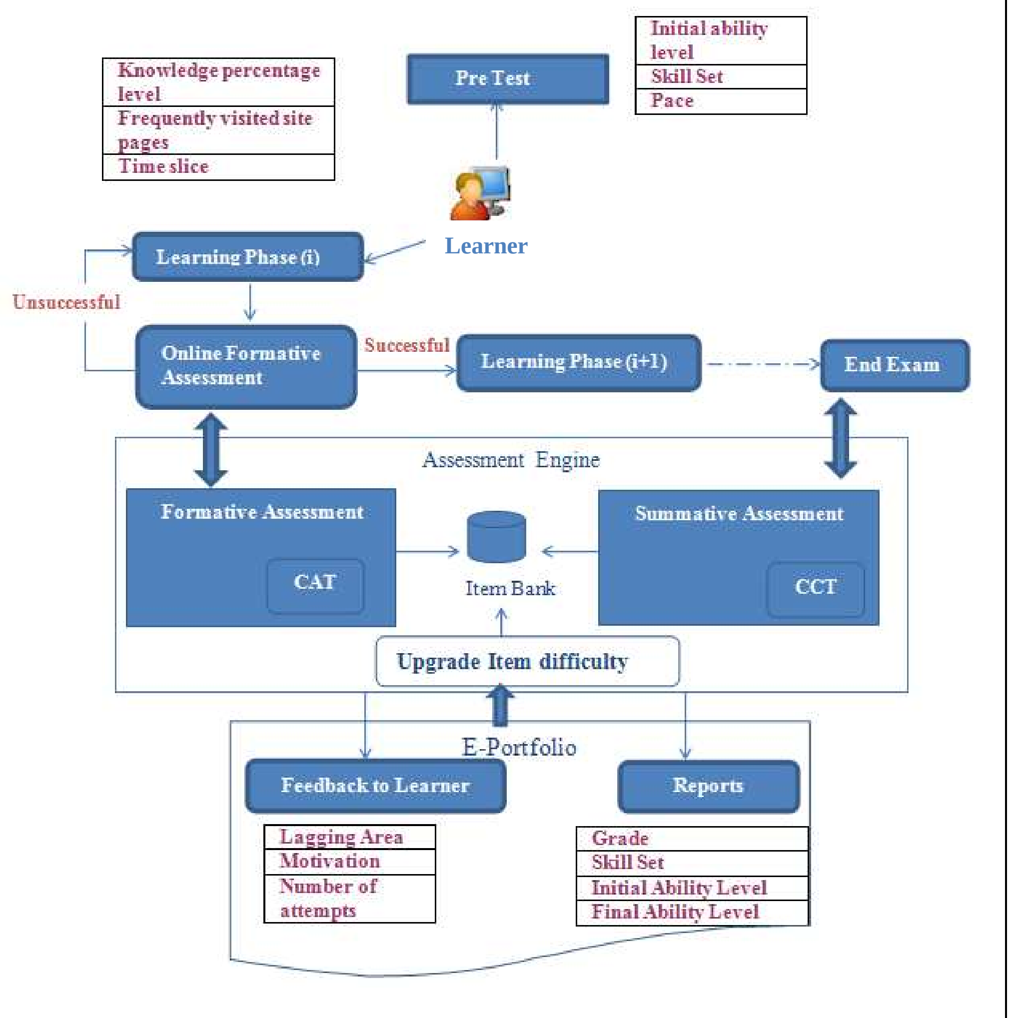

Figure2: Proposed Online Assessment

At each learning phase, formative assessment helps to identify and improve the learner's ability level and at the end of the course a summative assessment is used to provide the final results (score) of a particular course. For the summative assessment we need to take inputs from formative assessment which includes the number of attempts made by each learner, performance report, feedback which is available in e-Portfolio. Immediate score reporting facility is also available; once the test is completed the e-Testing system generates the reports where the ability levels (percentile) are shown for further improvement. Effective system feedback mechanism helps to upgrade the item's difficulty level which was given by the instructor at the time of creation.

In traditional learning scenario there is a possibility for the teacher to identify the students who have varied knowledge levels [low, average and good level]. And it is the fact that in any educational institution there will be a threshold value to get pass marks [ex: 40%] in any exam, which states that even though the student falls into lower ability set he is pass and there is a need to bridge the gap between the students with lower and higher ability levels. The important point here is after identifying the student's knowledge level what the instructor can do in order to raise the level. Based on this ability level more number of assignments/activities can be given to improve their skill, and providing feedback or motivating the student after taking the activity which serves better than after the end exam.

The main advantage of the proposed approach is to improvise the student skill set by using the ability level and within the stipulated time period encouraging the lower/average ability learner to take more number of quiz attempts may improve his/her ability level and the skill set. Under the formative assessment we have introduced self-assessment for quantifying the learner's ability, and in the rest of implementation work quiz resembles to the self-assessment. Self-assessment is one of the motives that drives self-evaluation, along with self-verification and self-enhancement which also helps the instructor to specific actions to bring the change.

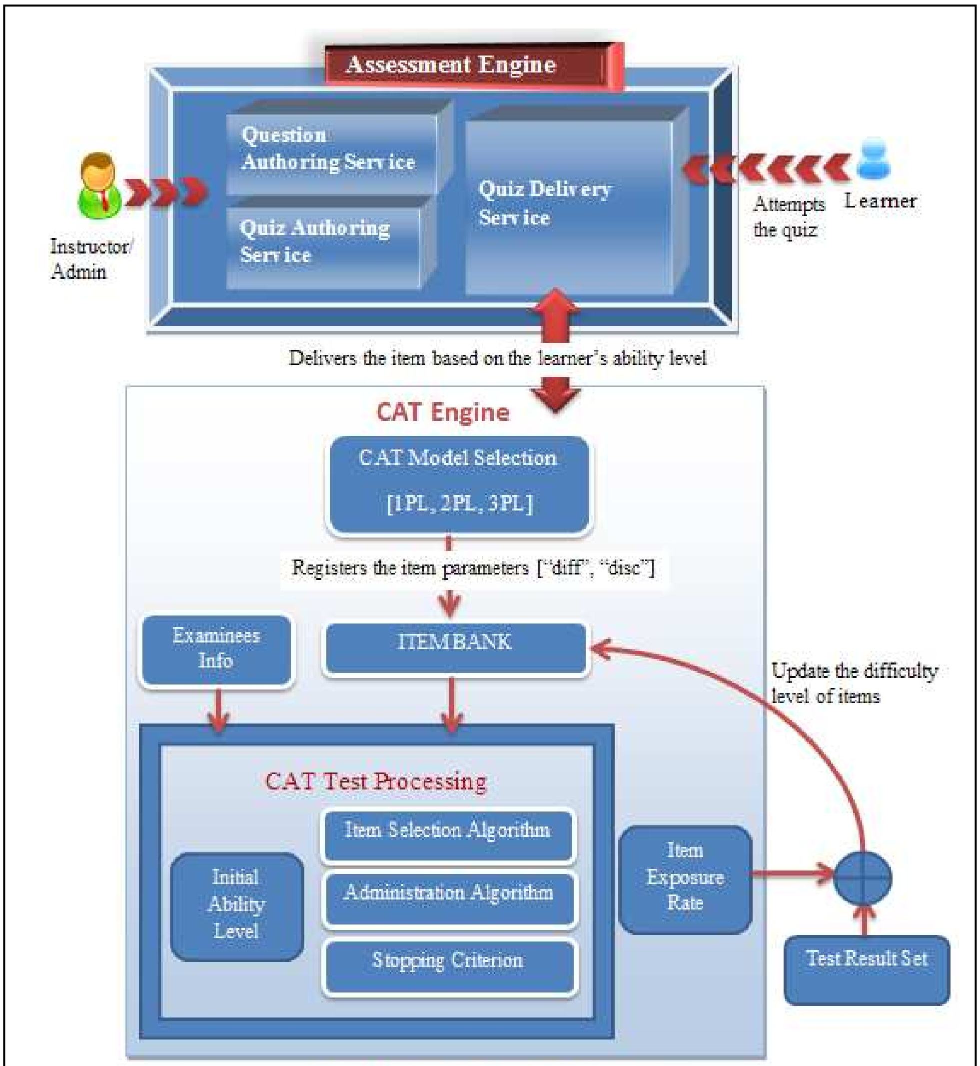

Figure 3: Creation and Delivery of Self-Assessment

A. Implementation work of the adaptive online assessment using CAT:

As part of the implementation on the proposed architecture, we have developed an assessment engine as web service based like question authoring, quiz authoring, quiz delivery are the three web services. Using the question authoring service, the instructor/admin has a privilege to create or upload QTI compliant questions before the course commencement. In assessment usage of multiple interaction types helps the examinee to understand the question clearly before answering it, so we have created 5 interaction types such as choice based (true/false, multiple choice), associate type (pairing up the choices), text entry (fill in the blanks), order type (making the correct sequence of options) and hotspot interaction types.

Quizzes are being created using the quiz authoring service where the difficulty parameter (b) of each item would be chosen. And the quiz would be delivered as part of course activity in the form of self-assessment. The advantage of assigning the difficulty level to each item during the quiz creation allows the instructor to select the same item for different classes of learners (same item can be delivered for the learner of junior class with lower difficulty and to senior class with higher difficulty). CAT engine has been developed as web service which would be invoked during the delivery of quiz. In order to reduce the load on the web services clients have been created using rich internet applications, where it utilize the processing capability of the client system.

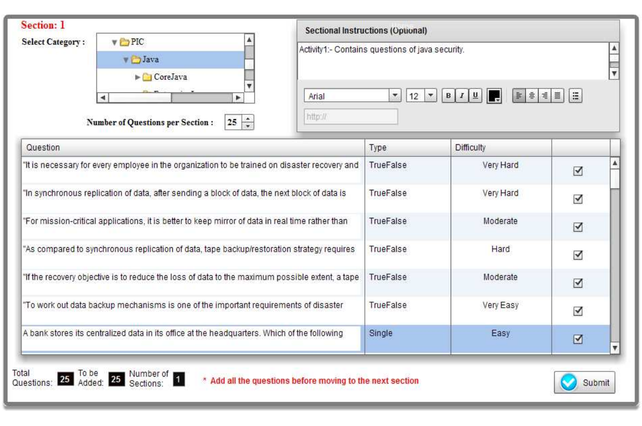

Figure 4: Quiz Creation user interface for the instructor

Initially CAT assumes that the examinee is of average ability, with that ability it will calculate the probability of giving correct answer for each Item using IRT models. From the calculated probabilities it will find the item which is having high probability and displays it to examinee. Evaluation of learners attempt is carried out in the quiz delivery service and the result is forwarded to CAT engine to calculate the ability level. The results of the self-assessment can be used by the instructor to check each individual's ability or certain groups of learners with varied ability levels. The ability level set which we considered in this model ranges from -2 to +2. For example if the instructor defined the threshold limit [ability is +1] for a course and a learner1 got -2.0, learner2 got 0.0 after the self-assessment.

It is the responsibility of the instructor to take necessary measures to improve the ability by increasing the number of activities within the stipulated time period. Let's say after 3rd activity it is observed that learner1's ability is 0.0 and learner2's ability is +1. It clearly states that learner1 is not able to acquire the threshold but there is an improved ability level [-2.0 to 0.0] and skill set. Feedback and motivation can be provided for each identified individual/groups of learner [the implementation work of feedback mechanism is not included in the figure-3].

Figure-3 depicts the work flow of the self-assessment creation and delivery, during the initialization of CAT engine the initial ability level is set to average i.e. 0.0 and the result of this test is used as the initial ability level for the next activity. As stated before 1-parameter model [which will be loaded by CAT model selection] is used to identify the learner's ability. After an item is administered, the CAT updates its estimate of the examinee's ability level.

If the examinee answered the item correctly, the CAT will likely estimate their ability to be somewhat higher, and vice versa which is decided by item selection and administration algorithms. The item exposure rate algorithm keeps track of how many times each item is administered (to any examinee). Using this item exposure rate the instructor can update the difficulty level of the items for next batch students.

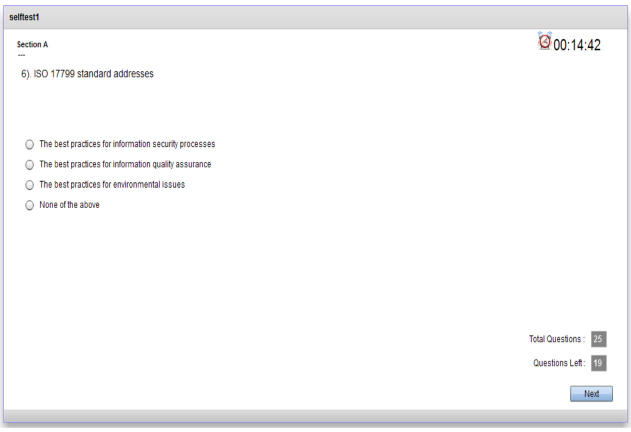

Figure 5: Quiz Delivery user interface for the learner

Item exposure rate = no of times item administered/no of examinees (4)

B. Web Mining in Online-Assessment

Web mining can be used for enhancing the learning process in online assessment; we can use web usage mining for finding patterns on learner's navigational behavior. These patterns of navigational behavior can be valuable while creating the knowledge structure of the user. This knowledge structure helps the user in revising the content visited in the form of a tree based view. Zaiane [4] studies on the use of machine learning techniques and web usage mining to enhance web-based learning environments for the educator to better evaluate the learning process and for the learners to help them in their learning task. Sung Ho Ha [7] dimension of discovery of association rules in web server to find all associations and correlations among the web pages allows learners to identify their knowledge structures and helps in reorganizing web space on these structures.

However, it is the usage information that actually reflects how a user is navigating or learning from the website. Such usage information can not only serve as a useful feedback to the experts about the learners approach, but can also suggest to learners from the navigation experience of other user's on what they found useful. The best knowledge structure can be recommended for the learners of similar interests or skill sets.

IV. Result Processing

At the end of formative assessment the data collected at each phase is used to calculate the percentile of the learner and in the summative assessment grades are formulated.

*Case Study-1: T*he two phase framework described in the above methodology can be implemented in the online learning environment. We can collect the initial attributes during the entrance exam of this course. At each learning phase, based on each learner performance the reports can be generated.

Table 1: Formative Assessment-I

ID	Course	Performance (%)	Strengths	Weakness
102	XYZ	44%	LR	PRS, PSS
109	XYZ	34%	-	LR, PRS, PSS
111	XYZ	67%	LR, PR	PSS

Here the performance is the ability level calculated using CAT methodology in the form of percentile. LR (Logical Reasoning skills), PSS (Problem Solving skills), PRS (Programming skills) are identified under each category.

The input for the summative assessment comes from the data collected at all the levels of formative assessment and the final test is configured. In table-2, the initial ability level is obtained from the entrance exam and the final (improved) ability level is obtained after the assessment. The grades are given according to the course criteria.

Table 2: Summative Assessment

ID	Course	Initial ability level	Final ability level	Grade	Skill set

102	XYZ	3	7	B+	LR, PRS
109	XYZ	2	6	B	LR, PRS
111	XYZ	7	9	A+	LR, PRS, PSS

Case Study -2:

In this case study, during the self-assessment the calculation of the learner ability using 1-parameter model is explained.

A two-item test will be used to illustrate the ability estimation process. Under a one-parameter model, the known item parameters are:

b = 0, a = 1
b = 2, a = 1

The examinee's item responses were:

Item	response (u)	difficulty (b)
1	1	0
2	0	2

A priori estimate of the examinee's ability is set to $\hat{\theta}_s = 0.0$

First iteration: Initial Theta=0.0

Item	u	P	Q	a(u-P)	a*a(PQ)
1	1	0.5	0.5	0.5	0.25
			Sum	*0.5*	*0.25*

$$\Delta\theta_s = \frac{\sum_{i=1}^{N} -a_i[u_i - P_i(\theta_s)]}{\sum_{i=1}^{N} a_i^2 P_i(\theta_s) Q_i(\theta_s)} \qquad (5)$$

$$\theta_{s+1} = \theta_s + \Delta\theta_s \qquad (6)$$

where θ_s is the estimated ability within iteration '*s*'

θ_{s+1} is the calculated ability within the iteration '*s*'

a_i is discrimination parameter of item i, i= 1,2,..N

u_i is the response made by the examinee to item i

u_i = 1 for a correct response

u_i = 0 for wrong response

$P_i(\theta_s)$ is the probability of correct response to item i

$Q_i(\theta_s)$ = 1- Pi(θs) is the wrong response

$\Delta\theta_s = 0.5/0.25 = 2.0$ (applying in equation 5)

$\theta_{s+1} = 0.0+2.0 = 2.0$ (applying in equation 6)

Standard Error [SE] = $1/\sqrt{(a * a (PQ))}$ (7)

$= 1/\sqrt{0.25} = 2.0$

Second iteration: new Theta=2

Item	u	P	Q	a(u-P)	a*a(PQ)
1	1	0.8807	0.1193	0 .1193	0 .105
2	0	0.5	0.5	-0.5	0.25
			Sum	*-0.3807*	*0.35506*

$\Delta\theta_s = -.3807/.35506 = -1.07219$

$\theta_{s+1} = 2.0+(-1.07219) = 0.92781$

SE = 1.6783

Based on the steps involved in CAT the test will be terminated when SE<0.01.

A. Enhancing the experience of feedback

In this procedure we have tabularized the attributes like lagging area, motivation message, number of attempts made, etc. Delivering feedback with the assistance of experts and peers, through their own reflection for deeper understanding of the knowledge and skills associated with a subject discipline and in ways that help students to self-correct.

Traditional forms of feedback all too often fail to engage learners either cognitively or emotionally, written comments on assignments are often too brief or difficult for the inexpert learner to interpret, and are frequently overlooked when the next assignment is due. Audio recorded individual feedback can be delivered to individual learners as personalized feedback, for example tips and hints for forthcoming assignments. Once a lengthy, time-consuming process, giving detailed feedback on dissertation drafts now takes place with less effort and in a shorter time.

B. Validity and reliability of the Assessment

Awarding assessment engines must ensure that assessment delivered and maintained by electronic means is fit for purpose and produces a valid and reliable measure of a learner's skills, perceived knowledge, pace, understanding capability and/or competence.

C. Security

It is necessary to consider the implications of security, confidentiality and authentication of the candidate either taking the test or submitting the work. There are significant implications for educational institutions and work based tracking of achievement though these issues are being addressed in a number of ways. Awarding assessment engines must maintain and review the security of e-assessment systems to ensure authentic test outcomes and protection against malpractices.

V. Conclusion and Future Work

In this paper, we have proposed an approach for making online assessment intelligent and described how the performance of individual learner can be improved by providing enhanced feedback mechanism. Applying adaptability to online assessment provides the right mix of technology and individualization that can enhance the learning experience. We have illustrated the benefits of applying psychometric models in online assessment and how it improves the learner skill set.

Future implementation and testing of the tool can be enhanced by incorporating an automated approach for guided personalization to improve the ability levels of the learner and the data identified in this approach can be used for effective personalization in e-Learning by using web mining techniques.

Acknowledgment

We are grateful to C-DAC, under Department of IT, Ministry of Communications & Information Technology, Government of India for supporting the research work carried out in eLearning.

References

[1] Lai, J., Cella, D.. Chang, C. H., Bode, R. K., & Heinemann, A. W. (2003). *Item banking to improve, shorten, and computerize self-reported fatigue*: *An illustration of steps to create a core item bank from the FACIT-Fatigue scale*. Quality of Life Research, 12, 485-501

[2] Dodeen, H. (2004). *The relationship between item parameters and item fit*. Journal of Educational Measurement, 41, 261-270.

[3] Brusilovsky, P., & Pesin, L. (1994). *An intelligent learning environment for CDS/ISIS users*, Proceedings of the interdisciplinary workshop on complex learning in computer environments, Joensuu, Finland

[4] O. Zaiane, M. Xin, and J. Han. *Discovering Web Access Patterns and Trends by Applying OLAP and Data Mining Technology on Web Logs*, In Proceedings of the Advances in Digital Libraries Conference, pages 19 -29, 1998.

[5] Meteren, R. V., & Someren, M. V. (2000). *Using Content-Based Filtering for Recommendation*, MLnet / ECML2000 Workshop, May Barcelona, Spain.

[6] R. Cooley, B. Mobasher, J. Srivastava, *Web Mining: Information and Pattern Discovery on the World Wide Web*, IEEE, 1997.

[7] Sung Ho Ha, Sung Min Bae, Sang Chan Park, *Web Mining for Distance Education* on ICMIT 2000.

[8] Georgios Lappas, *An Overview of Web Mining in Societal Benefit Areas* on the 9th IEEE International Conference on E-Commerce 2007.

[9] IMS Question and Test Interoperability specification http://www.imsglobal.org/question

[10] Chong Ho Yu. *A Simple guide to the Item Response Theory (IRT) and Rasch Modeling*, 2010

[11] Khribi, M. K. Jemni, M., & Nasraoui. O. (2008). *Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and Information Retrieval*. The 8th IEEE International Conference on Advanced Learning Technologies, July 1-5, Santander, Spain

[12] Sandesh Jain, Dhanander K Jain, Harihar Bhojak, Ankit Bhilwar, Mamatha J. *Personalization of e-Learning services using Web Mining and Semantic Web*. The 3rd International Conference on Machine Learning and Computing [ICMLC] 2011, Singapore.

[13] Margit Antal, Levente Eros, Attila Imre, *Computerized adaptive testing: implementing issues*, ACTA Univ. SAPIENTIAE, Informatica 2010.

[14] Deborah Harris, *An NCME Instructional Module on Comparision of 1-, 2-, and 3-Parameter IRT Models*.

[15] Hambleton, R.K., H. Swaminathan, and H.J. Rogers, *Fundamentals of Item Response Theory*, SAGE, Newbury Park, C A, 1991.

Author Biographies

Uday Kumar Mothukuri received his Bachelor's degree and Master's degree in Information Technology from Jawaharlal Nehru Technological University, India. He is currently working with Centre for Development of Advanced Computing, Government of India. His areas of interest include eLearning, Data Mining, Scripting languages and Web Technologies.

Swathi Murukutla received her Master's Degree from JNTU, Hyderabad in Computer Science Stream. She is currently working with Centre for Development of Advanced Computing, Government of India. Her areas of interest include Image Processing, Web-Technologies and eLearning.

Sandesh Jain received his Bachelor's degree from RGPU, Bhopal in Information technology. He is now currently working as Technical Officer and leading the Personalized eLearning Team at Centre for Development of Advanced Computing, Government of India. He also acted as Co-Investigator for several government funded projects. His areas of interest are Web Technologies, eLearning, Cloud computing, Data Mining and Data warehousing.

Dhanander K Jain received his Bachelor's degree from Thapar Engineering College, Patiala in Electronics and Telecommunications. He has over 30 years of experience in R&D, Training and Project Planning, Coordination, Implementation and currently working as Director at Centre for Development of Advanced Computing at Hyderabad. His areas of interest include Ubiquitous computing, Information Security, Embedded Systems design & VLSI design, Wireless Sensor Networks, eLearning & Education Technologies.