Aug. 31

International Journal of advanced studies in Computer Science and Engineering
IJASCSE Volume 4, Issue 8, 2015

A Comprehensive Study on Intelligent Tutoring Systems

N.Sharada
Research Scholar, Dept. of CS&SE
Andhra University,
Visakhapatnam, India

M.Shashi
Professor, Dept. of CS&SE
Andhra University
Visakhapatnam, INDIA

D.Madhavi
Professor, Dept. of CSE
Dr.L.B.College of Engineering (W)
Visakhapatnam, INDIA

***Abstract*— In recent years, with the introduction of new technologies and gadgets, the world around us is undergoing technology revolution. Hence with the aid of new tools and techniques it is time to revamp our educational system to benefit the system of learning. Educational data is becoming increasingly rich as more and more educational systems are going online and collecting large amounts of data, thus opportunities for knowledge discovery in education data have increased tremendously. Educational Data Mining (EDM) is an emerging multidisciplinary field exploring data in educational context by applying different DM techniques. It provides inherent knowledge of teaching and learning process for effective education planning. Intelligent Tutoring System is an effective computer based software to provide customized instructions to students according to their cognitive abilities. The purpose of this study is to discuss the importance of EDM and current trends of data mining in education research. An overview of various Intelligent Tutoring Systems (ITS) emphasizing on their features are provided. In addition a case based intelligent tutoring system is demonstrated. Several limitations of existing research are discussed and some directions for future research trends are suggested.**

Keywords- Educational Data Mining (EDM), Data Mining (DM), E-Learning, Intelligent Tutoring System (ITS)

I. INTRODUCTION

The number of educational institutions has increased many times in the last few decades. A large number of students are graduating every year. Despite of the fact that the best of teaching methods are being followed, institutions still face challenges from drop out students, low academic achievers, and unemployed students. Educational Data Mining (EDM) is an emerging multidisciplinary field exploring educational data in order to improve the student's performance. EDM employ not only data mining techniques such as classification, clustering, association rule mining, sequential mining, text mining but also other statistical approaches such as regression, correlation, visualization etc. Learner behavior is captured well by integrating psychometric models in Education Data Mining. The main objective is to help the teacher to adapt the teaching methods by exploring issues such as study the different learning patterns, study the reasons for the disparities in the student performance, understanding the characteristics of students etc. The prediction of academic performance helps in identifying slow learners so that some form of timely remediation may be offered to them. For web based courses this prediction attains higher importance due to the lack of face to face interaction between instructor and student. The academic performance of student depends on many factors such as previous academic records, family background, economic status, health issues, attendance, etc. Though less probable, the performance of some students may be also influenced by their physical, mental or learning disabilities. Educational data mining has emerged as an independent research area in recent years, with the establishment of the annual International Conference on Educational Data Mining, and the Journal of Educational Data Mining. In particular, the advent of public educational data repositories such as the PSLC DataShop and the National Center for Education Statistics (NCES) data sets has created a base which makes educational data mining highly feasible. Educational institutions collect huge amount of student details but most of this data remain unexplored and unutilized in the decision making process of the institution. However if the circumstances for poor performance are determined well in advance then this knowledge can be utilized in progressive decision making process. This information will help teachers to customize their instruction as per the students learning pace and hence provide better guidance. Students will be able to classify their strengths and weaknesses and thereby they can target on maximizing their strengths and minimizing their weakness.

In the present digital age, the world of education is undergoing a massive transformation. The new technologies and gadgets not only enrich and enhance our existing education system but also provide new opportunities which can make the process of learning beyond institutions and allow learners to learn what they want to learn, when they want to learn, and how they want to learn[1]. Data Mining has shown noteworthy results in numerous fields such as business intelligence, intrusion detection, bioinformatics and lately attempts are on to apply data mining techniques in the education domain which is commonly known as Educational Data Mining (EDM). Learning environments can be broadly classified into three categories: traditional class room based system, e-learning, and Intelligent Tutoring Systems. In conventional systems statistical techniques have been applied on the administrative data collected from schools and universities and data that was gathered in class room environments. E-Learning provides online instruction and have opened up new opportunities to collect student data and apply web mining techniques. Technology enhanced learning depends more on Learning Management System (LMS) or Course Management Systems (CMS). These LMS/CMS record the key strokes of individual users as server logs. Mining these logs provide patterns which help teachers to identify slow learners and can plan teaching strategies. Intelligent Tutoring System (ITS) in contrast to traditional programs, have the ability to adapt to the needs of each individual learner. It has already been shown that the best teaching is individualized learning (Benjamin Bloom, educational psychologist 1984). This survey paper discusses various issues and challenges in EDM and is organized as follows. Section II architecture of general intelligent tutoring system is studied, Section III features and structural organization of popular ITS is elaborated. Section IV discusses the most popular research trends in education that has been resolved using DM techniques. Section V demonstrates case study. Section VI describes the most prominent future research lines and conclusions are outlined.

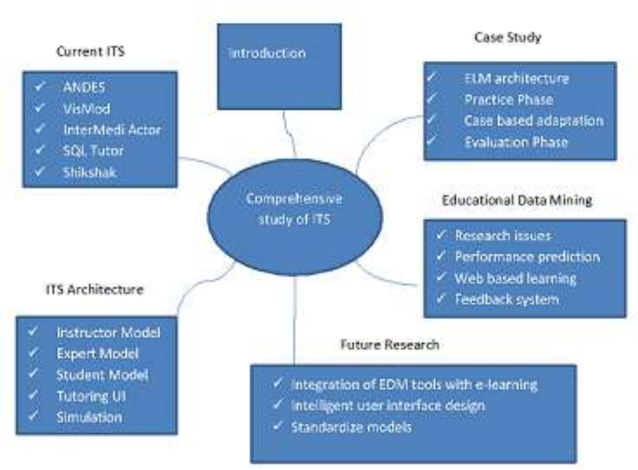

Figure 1: Schematic Diagram

II. ARCHITECTURE OF INTELLIGENT TUTORING SYSTEMS

In traditional classroom based approach, teaching follows a teacher specific fixed method and pace. However, a heterogeneous group of students in such classrooms will have different requirements. Hence, such a method of teaching might not be optimized for the individual students. In 1984, Benjamin Bloom defined the "two-sigma problem," which states that students who receive one-on-one instruction perform two standard deviations better than students who receive traditional classroom instruction. An improvement of two standard deviations means that the average tutored student performed on par with the top 2 percentile of those receiving classroom instruction. Providing a personal training assistant for each learner is beyond the training budgets. However, a virtual training and practice assistant that can integrate the concepts of the subject and teaching expertise of experienced trainers provides a new option. The intelligent tutoring systems (ITS) has been pursued for more than three decades by researchers in education, psychology, and artificial intelligence. Today, operational ITS systems provide practice-based instruction to support corporate training, college education, and military training. The main advantage of Intelligent Tutoring System is it can provide personalized instructions to students according to their cognitive abilities. The classical model of ITS architecture is shown in Fig.2 has three main modules – Expert model, Instructor model and Student model.

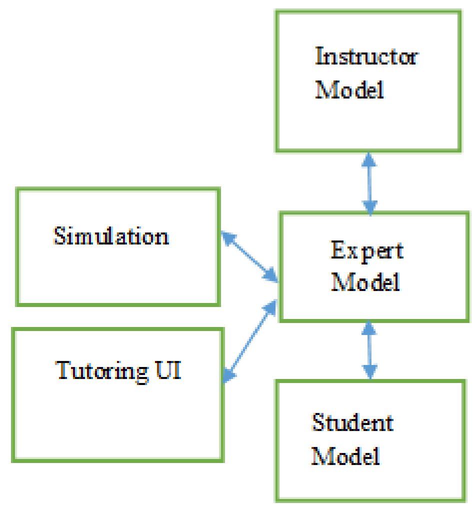

Figure 2: Architecture of ITS

An expert model is a computer representation of a domain expert's subject knowledge and problem-solving ability. This knowledge enables the ITS to compare the learner's actions and selections with those of an expert in order to evaluate and understand what the user knows. A variety of artificial intelligence (AI) techniques are used to capture how a problem can be solved. The student model evaluates each learner's performance to determine his or her knowledge, perceptual abilities, and reasoning skills and expertise. Based on the student model, instructor model tailors teaching strategies, in terms of both the content and style, provide explanations, hints, examples, demonstrations, and practice problems as needed.

III. CURRENT INTELLIGENT TUTORS

The structural organization of influential intelligent tutors in various domains [32] is discussed in this section.

ANDES (physics):-Andes [2] was developed to teach physics for the students in Naval Academy. Bayesian networks were primarily used in Andes for decision making tasks. The major foci of the system are (1) Select the most suitable strategy for the student (2) Predict Student's actions (3) Perform a long term assessment of the student's domain knowledge. Andes is a domain dependent ITS. Each problem in the system is broken into steps and Bayesian network is formed using those steps as nodes. The Bayesian network would predict the most probable path for the student during a course. Each student could have different approaches to a problem, the network would be adjusted accordingly (the probabilities would change) and finally for a new problem it would predict the best strategy for the student. There is also a problem-solver in the system. This problem solver partially or wholly solved a problem to help the students. Personalized help is available for 500 online physics homework problems.

ViSMod:-ViSMod [3] system uses Bayesian network with three levels of hierarchy. At the top level the concepts to be taught were represented in a hierarchical manner and in the second level student's performance and behavior were described and the third level nodes represent analysis of student's performance. In this tutor only the first level is domain dependent, and the other two levels remain same for different domains. The student can observe only the top two levels of the Bayesian net and third level is only visible to the teachers. Hence during the course the probabilities in the second and third level of the Bayesian net changes according to the student's performance and these probabilities changes the first level values. Hence the probability values in the first level were directly dependent on the two lower levels. After the probabilities were computed the most probable path along the first level was determined and the first node of the most probable path was chosen as the next step in the course.

InterMediActor:-InterMediActor [4] uses fuzzy inference mechanism and implemented *navigation graph*, data structure. This graph determines which concept comes after which. In the case of multiple choices, decisions are made using fuzzy rules. The fuzzy rules map the student's capability with the concept, to decide whether the concept is suitable for the student or not. The student's information and other related information of the topic and concept are described in the form of fuzzy sets. The fuzzy rule base establish relationship between them and thereby help to select the most probable concept next.

SQL-Tutor:-SQL-Tutor [5] is used to teach university students Structured Query Language (SQL). Artificial Neural Network (ANN) are used in SQL-Tutor for decision-making. ANN model is designed to analyze the student and select an appropriate problem from the database. The solutions to the problems are represented in the form of constraints. When a student submit a solution then the system calculates the correctness by checking the number of constraints violated by the student. The next problem to be chosen or any other teaching decision is based on this information. The ANN used is a feed-forward network and has four inputs, one output and a hidden layer. Delta-bar-delta back propagation and linear tanh (LT) transfer function is used and the inputs consist of student information such as (1) Time needed to solve the problem, (2) The level of help provided to the student (3) The complexity of the problem (4) the knowledge level of the student. This system also provides hints, partial solution or complete solution as required.

C++ Tutor:-C++ Tutor is a rule-based ITS [6] Here the C++ concepts are represented as rules in the form of Horn sentences called the *Theory*. The problems are represented as feature vectors. The students should choose the correct label from a set of possible labels. Then the algorithm *NEITHER* modifies the rule base reflecting the student's state of understanding, representing the student's correct knowledge as well as the misconceptions. This process is called *Theory-revision*. After the theory-revision is complete then the system explain the bugs in student's concept with examples.

Shikshak:-Shikshak [7] is organized in three modules – *Domain Model*, *Student Model and Control Engine*. Domain model is the knowledge base of the system, where the domain knowledge is organized for all the subjects to be taught by the system. The *Domain Model* consists of a Domain Organization Module and a Repository. Domain organization module is a structural representation of the different courses and their components stored in the system. Two major data structures are used for this purpose. Course Tree (CT) is a hierarchical structure of a course. The tree root node define the course name and the leaf nodes represent topics which are atomic teachable units. **Topic** Dependency Graph (TDG): The nodes of TDG represent the topics from the corresponding CT, whereas the edges in TDG depict 'prerequisite' relation between the nodes (topics). The Repository is a pool of learning and testing materials. *Student Model*: The students' performance and learning pattern has been modeled in the present system as a Fuzzy State Transition Machine **<S, I, δ>**, where **S** is the set of states, **I** is the set of inputs and **δ** is the transition function.

IV. DISCUSSION ON EDUCATIONAL DATA MINING RESEARCH ISSUES

EDM researchers [8, 9] view the following as the goals for the educational research.

Academic Goals:

- Person specific goals:
  - Student performance addresses cognitive learning abilities, student performance analysis based on knowledge levels, motivation, and attitudes.

  - Faculty performance involves interpretation and prediction of student academic performance, fine tune teaching strategies according to the student learning abilities.
- Institute specific goals deals with introducing new courses according to industry requirements, predict enrolment of students for a particular course.
- Domain specific goals aim at discovering or improving domain models that describe the content to be learned and optimal instructional sequences.

Administrative Goals:

- To maximize resource utilization (human resources as well as infrastructure) and to maintain industry academia relationship,
- Advancing *s*cientific knowledge about learning process and learners through building computational models.
- To explore intelligent tools and techniques used in EDM.
- Identify the challenges in EDM.

To accomplish these goals and for quality education delivery, educational mining research uses data mining techniques like prediction, clustering, association mining, modeling etc. The practice guide of the Institute of Education Sciences [10], recommends educators to analyze student data to track academic progress and understand which instructional practices are effective. This paper presents a review of various research issues of EDM under the following categories:

- Student feedback: Interpret and understand student behavioral information.
- Student modeling: To estimate student knowledge based on his/her cognitive abilities.
- Predicting student performance: Predict and estimate student academic outcome.
- Recommendation for students: Provide academic advice to student.

Student Feedback:-The data mining techniques [11] used in Intelligent Tutoring System describe, interpret and predict behavior, and evaluate progress in relation to learning outcomes. Student's behavior models are used to improve their experience with intelligent tutoring system. The model captures the amount of time spent on each problem and how this changes over the course of a session and also identifies unobservable factors such as student engagement in solving problems. Learning decomposition, an educational data mining technique [12] is applied to determine the relative efficacy of different instructional strategies. Logistic regression is used to determine how much learning is caused by different methods of teaching the same skill, relative to each other. ASSISTment is used for middle school and high school math problems. Fuzzy Rules [13] are discovered which describe the relationships between the student's usage of the different activities provided by the e-learning system and final marks obtained in the courses. These rules can help the teacher to discover beneficial relationships between the use of web-based educational resources and the student's learning. Subgroup Discovery Iterative Genetic Algorithm (SDIGA) an evolutionary model for the extraction of fuzzy rules is applied to e-learning system. Data mining [14] and knowledge discovery techniques are applied in this study to find interesting relationships between attributes of learners, assessments, the solution strategies adopted by learners and so on. Since Web-based Mobile-Learning System collects vast amounts of learners profile data, they developed a new data-mining algorithm, called ARGA (Association rules based on an improved Genetic Algorithm), to mine the association rules from a Web-based Mobile-Learning system. To improve Web-Based Education [15] evolutionary algorithms are used to discover relationships in student's usage data. Such knowledge is very useful for teachers and course authors to select the most appropriate modifications to improve the effectiveness of the course. Grammar-Based Genetic Programming (GBGP) with multi-objective optimization techniques is used to discover prediction rules.

Student modeling:-Corbett & Anderson's Bayesian Knowledge Tracing Model [16] is one of the most popular methods for estimating students changing knowledge state during skill acquisition. Student model stores all the information including his/her cognitive state about subject domain. The Q-matrix method [17] has been used to create concept models that represent relationships between concepts and questions, and to group student's test question responses according to concepts. These models are then used to both understand student behavior and direct learning paths for future students. An algorithm [18] to estimate Dirichlet priors has been developed to produce model parameters that provide a more plausible picture of student's knowledge. For the study, data from ASSISTment, a web-based math tutoring system is used. A new method [19] is proposed for instantiating Bayesian Knowledge Tracing, using machine learning to make contextual estimations of the probability that a student has guessed or slipped. Knowledge Tracing Model [20] is extended by considering class information, and learns four parameters: prior knowledge, learn, guess and slip for each class of students enrolled in the system. This approach considers the learner's classmates as a viable source of information for predicting the learner's behavior.

Predicting Student Performance:-The Genetic Algorithm [21] is proposed to improve the accuracy of combined classifier to predict student's performance based on features extracted from logged data. This method is useful in identifying students at risk early, especially in very large classes, and allow the instructor to provide appropriate advising in a timely manner. A grammar guided genetic programming algorithm [22] has been applied to predict if the student will fail or pass a certain course and identifies activities to promote learning in a positive or negative way from the perspective of Multiple Instance Learning (MIL). A methodology [23] is proposed for developing functions that predict student scores and dynamic testing metrics are developed from log data. Prediction functions can be used throughout the year, in order to provide timely and valid feedback to teachers and schools about student progress. A Bayesian Network approach [24] is proposed for predicting cumulative Grade Point Average based on applicant background at the time of admission. Performance prediction models can also be built by applying data mining techniques to enrollment data. Ramaswami et al [25] developed a predictive data mining model to identify the factors causing poor performance in higher secondary examination in Tamil Nadu, India.

Recommendation for Students:-A Bayesian method [26] with similar permutation analysis techniques has been used to determine the most appropriate sequence of learning topics for effective learning among the students. To promote learning efficiency and effectiveness [27] a personalized courseware recommendation system (PCRS) based on the fuzzy item response theory (FIRT), is proposed which can recommend courseware with appropriate difficult level to learner. Since it is difficult and time consuming for teachers to give personalized suggestions to each student [28], particularly when there are many students in class. Concept-effect relationship model (CER) tool has been developed to identify the learning difficulties of students. A Personalized Instructing Recommendation System (PIRS) [29] has been designed for Web-based learning. This system recognizes different patterns of learning style and Web using habits through testing the learning styles of students and mining their Web browsing logs.

V. CASE STUDY ON CASE BASED ITS

Case Based Reasoning (CBR) is analogy based problem solving approach in artificial intelligence. In this new problems are solved based on the solutions of similar past problems. The structure of a case consists of a problem description and a solution. Case Based ITS constitute the following phases:

1. Practice phase: Finding a similar problem solved in the past to provide learner a problem solving environment.

2. Case-Based Adaptation: Allows interactive system to adapt to a specific user (Student).

3. Case-Base Teaching: Assists the learner by providing useful cases for learning new information.

There are several applications for case based intelligent tutoring systems the most significant are medicine, project management, economics, programming, game playing etc., Weber et al developed an Episodic learner model which performs the following functions.

1. Stores knowledge about the user in terms of a collection of episodes which can be viewed as cases.

2. Every solution stated by the user is diagnosed completely or partially to find problem errors.

3. Keeps track of the used components and the usage level at various stages.

ELM-ART (Episodic Learner Model- Adaptive Remote Tutor) is a web based ITS [30] to support learning programming in LISP. This system makes use of Episode Learner Model. The architecture of ELM is depicted in the fig. 3.

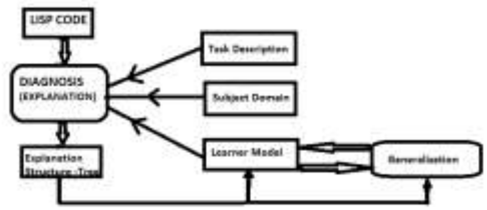

Figure 3: ELM Architecture.

Subject domain consists of rules and concepts in the form of hierarchically organized frames. Concepts comprise knowledge about the programming language LISP, common algorithms and problem solving knowledge. Concepts in turn consist of plan transformation leading to semantically equivalent solutions and a set of rules. Rules describe different ways to solve the goal stated by the concept and bug rules. In Fig.4 the left Panel displays a list of lessons/topics and the panel on the top provides options like Communication window, evaluator, Help on the current topic and Search facility. Through communication window one can discuss their ideas with other participants and with the tutor. An important feature of ELM-ART is that the system can predict the student way of solving a particular problem and find the most relevant example from the individual learning history. This kind of problem solving support is very important for students who have problems with finding relevant examples.

Figure 4:Prompt by the system immediate evaluation

If the student failed to complete the solution of the problem, the system provides a sequence of help messages with detailed explanation about the error. Help on the current topic shows an overview containing all pages that are prerequisites to understand the topic of the current page. The search facility lets the learner search for all topics and keywords that may appear in the content of the course. The evaluator window displays learner's performance in learning the course at different instances of time. Pushing this button, the learner can inspect statistics of all the worked out exercises and tests.

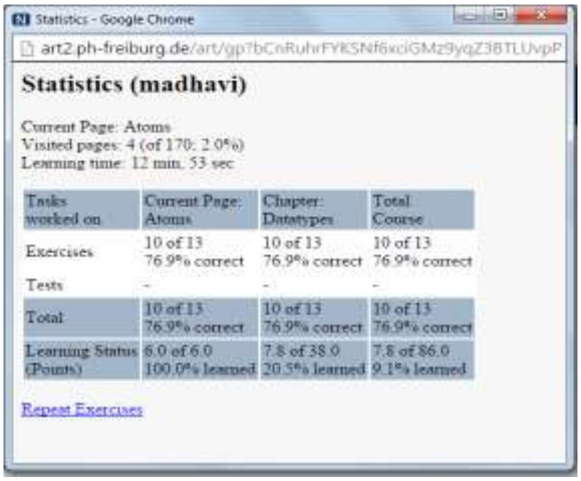

Figure 5: Evaluation chart of student madhavi.

Fig. 7 depicts example of adaptive annotation of links at the beginning of the course. The metaphor is traffic lights. Red means not ready to be learned based on the prerequisite conditions of different topics/links, green means ready and recommended, yellow means ready but not recommended. ELM-ART provides intelligent access to hypermedia-structured learning material and problem solving support. ELM-ART integrates the features of an electronic textbook, of a learning environment, and of an intelligent tutoring system. Hinting is an effective tutoring technique that helps the students to recall the rules or facts, particularly when the student has difficulty in solving a problem. In many tutoring systems, the tutoring software extends hints instantaneously when the student is in need of help, e.g. Andes (Gertner et al., 1998).

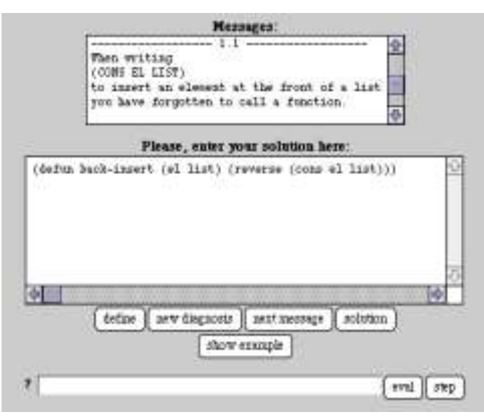

Figure 6: Intelligent problem solving support learning in ELM-ART

Figure 7: Annotation Links for user convenience

However, ELM-ART system provides manual intervention based support to the students in the diagnosis of the code in its current state. A sequence of offline help messages with detailed explanation about the error are provided in response to the students request message. Effective tutoring systems should monitor student engagement during problem solving and apply strategies to maintain student's attention when the engagement decreases. Lepper and Woolverten have claimed that individualization, immediacy and interactivity are the three major factors that enable expert tutors to be more effective than traditional learning in the classroom.

VI. FUTURE RESEARCH TRENDS

This study provide some useful insights for researchers and educators in improving educational system. Still there are lot of new possibilities to be considered in EDM, the most significant and influential aspects among them are reviewed. In most of the present EDM tools the educators have to select specific data mining algorithm and have to provide appropriate parameter values for good results. In the future EDM tools have to be designed to be easier for non-technical users or educators and also have an intelligent user interface in order to automate data mining tasks. EDM will be much more widely used by educators, when results obtained from data mining techniques could be easily integrated into the e-learning environment. Current ITS are domain specific and once build they can't be modified without the intervention of the system developer. Therefore standardization of educational data and output model are needed.

REFERENCES

[1] Collins, Allan, and Richard Halverson. "Rethinking education in the age of technology: The digital revolution and schooling in America" Teachers College Press, 2009. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[2] Gertner, Abigail S., and Kurt VanLehn. "Andes: A coached problem solving environment for physics." *Intelligent Tutoring Systems*. Springer Berlin Heidelberg, 2000.K. Elissa, "Title of paper if known," unpublished.

[3] Zapata-Rivera, Juan-Diego, and Jim E. Greer. "Interacting with inspectable bayesian student models." *International Journal of Artificial Intelligence in Education* 14.2 (2004).127-163.

[4] Kavcic, A., Pedraza-Jiménez, R., Molina-Bulla, H., Valverde-Albacete, F. J., Cid-Sueiro, J., & Navia-Vázquez, A. (2003). "Student modeling based on fuzzy inference mechanisms" (Vol. 2, pp. 379-383). IEEE.

[5] Mitrovic, Antonija, Pramuditha Suraweera, Brent Martin, and Amali Weerasinghe. "DB-suite: Experiences with three intelligent, web-based database tutors." (2004).

[6] Baffes, Paul T., and Raymond J. Mooney. "A novel application of theory refinement to student modeling." *AAAI/IAAI, Vol. 1*. 1996.

[7] Chakraborty, S., Devshri Roy, and Anupam Basu. "Shikshak: An Architecture for an Intelligent Tutoring System." *Proc.* 16th International Conference on Computers in Education, Taipei, Taiwan. 2008.

[8] Baker, R. S. J. d. 2011. "Data Mining for Education." In International Encyclopedia of Education, 3rd ed., edited by B. McGaw, P. Peterson, and E. Baker. Oxford, UK: Elsevier.

[9] Romero, C., & Ventura, S. (2010). "Educational data mining: a review of the state of the art". Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 40(6), 601-618.

[10] Hamilton, L., R. Halverson, S. Jackson, E. Mandinach, J. Supovitz, and J. Wayman. 2009. "Using Student Achievement Data to Support Instructional Decision Making" (NCEE 2009-4067).Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance.

[11] Beal, Carole R., and Paul R. Cohen. "Temporal data mining for educational applications." *PRICAI 2008:* Trends in Artificial Intelligence. Springer Berlin Heidelberg, 2008. 66-77.

[12] M. Feng, J. E. Beck, and N. T. Heffernan, "Using learning decomposition and bootstrapping with randomization to compare the impact of different educational interventions on learning," in *Proc. Int. Conf. Educ. Data Mining*, Cordoba, Spain, 2009, pp. 51–60.

[13] C. Romero, P. Gonzalez, S. Ventura, M. J.Jesus, and F. Herrera, "Evolutionary algorithms for subgroup discovery in e-learning: A practical application using Moodle data," Expert Syst. Appl. J., vol. 36, pp. 1632–1644, 2009.

[14] S. Zheng, S. Xiong, Y. Huang, and S.Wu, "Using methods of association rules mining optimization in web-based mobile learning system," in Proc. Int. Symp. Electron. Commerce Security, Guangzhou, China, 2008, pp. 967–970.

[15] C. Romero, S. Ventura, and P. De Bra, "Knowledge discovery with genetic programming for providing feedback to courseware author," User Model. User-Adapted Interaction: J. Personalization Res., vol. 14, no. 5, p. 425-464, 2004.

[16] Corbett, A.T., Anderson, J.R., 1995. "Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge". User Modeling and User-Adapted Interaction, 4, 253-278.

[17] T. Barnes, "The q-matrix method: Mining student response data for knowledge," in Proc. AAAI Workshop Educ. Data Mining, Pittsburgh, PA, 2005, pp. 1–8.

[18] D. Rai, Y. Gong, and J. E. Beck, "Using Dirichlet priors to improve model parameter plausibility," in Proc. Int. Conf. Educ. Data Mining, Cordoba, Spain, 2009, pp. 141–150.

[19] Baker, R.S.J.d., Corbett, A. T., Aleven, V.: "More Accurate Student Modeling through Contextual Estimation of Slip and Guess Probabilities in Bayesian Knowledge Tracing." In: Woolf, B., Aimeur, E., Nkambou, R., Lajoie, S. (Eds.) ITS 2008. LNCS, vol. 5091/2008, pp. 406-415. Springer, Berlin Heidelberg (2008).

[20] Wang, Y., Beck, J.: "Class vs. Student in a Bayesian Network Student Model". In: Lane, H. C., Yacef, K., Mostow, J., Pavlik, P. (Eds.) AIED 2013. LNCS, vol. 7926/2013, pp. 151-160. Springer (2013).

[21] B. Minaei-bidgoli, D. A. Kashy, G. Kortmeyer, and W. F. Punch, "Predicting student performance: An application of data mining methods with an educational Web-based system," in Proc. Int. Conf. Frontiers Educ., 2003, pp. 13–18.

[22] A. Zafra and S. Ventura, "Predicting student grades in learning management systems with multiple instance programming," in Proc. Int. Conf. Educ. Data Mining, Cordoba, Spain, 2009, pp. 307–314.

[23] N. Anozie and B. W. Junker, "Predicting end-of-year accountability assessment scores from monthly student records in an online tutoring system," in Proc. AAAI Workshop Educ. Data Mining, Menlo Park, CA,2006, pp. 1–6.

[24] P. Haddawy, N. Thi, and T. N. Hien, "A decision support system for evaluating international student applications," in Proc. Frontiers Educ. Conf., Milwaukee, WI, 2007, pp. 1–4.

[25] Ramaswami, M., and R. Bhaskaran. "A CHAID based performance prediction model in educational data mining." arXiv preprint arXiv:1002.1144 (2010).

[26] Z. Pardos, J. E. Beck, and N. Heffernan, "Determining the significance of item order in randomized problem sets," in Proc. Int. Conf. Educ. Data Mining, Cordoba, Spain, 2009, pp. 111–120.

[27] C. Chen, L. Duh, and C. Liu, "A personalized courseware recommendation system based on fuzzy item response theory," in Proc. IEEE Int. Conf. E-Technol., E-Commerce E-Service, Washington, DC, 2004, pp. 305–308.

[28] Al-Sarem Mohammed, Mostafa Bellafkih, Mohammed Ramdani, "Improving Learning Performance by Providing Intellectual Suggestions**",** in International Journal of Computer Applications (0975 – 8887) Volume 31– No.5, October 2011.

[29] L. Zhang, X. Liu, and X. Liu, "Personalized instructing recommendation system based on web mining," in Proc. Int. Conf. Young Comput. Sci., Hunan, China, 2008, pp. 2517–2521.

[30] Weber, Gerhard, and Peter Brusilovsky. "ELM-ART: An adaptive versatile system for Web-based instruction." International Journal of Artificial Intelligence in Education (IJAIED) 12 (2001): 351-384.

[31] Lepper MR, Woolverton M. "The wisdom of practice: lessons learned from the study of highly effective tutors" In: Aronson J., editor. Improving Academic Achievement. New York: Academic; 2002. pp. 135–158.

[32] Chakraborty, Sunandan, Devshri Roy, and Anupam Basu. "Development of knowledge based intelligent tutoring system." Advanced Knowledge Based Systems: Model, Applications & Research 1 (2010): 74-10