DEVELOPING STUDENT MODEL FOR INTELLIGENT TUTORING SYSTEM

PURUSHOTHAMAN RAVICHANDRAN

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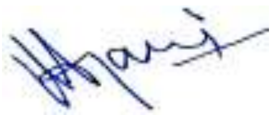
DECLARATION

Name: **Purushothaman Ravichandran**

Matriculation Number: **CGSIN00109212**

I hereby declare that this thesis is the result of my own work, except for quotations and summaries which have been duly acknowledged.



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ABSTRACT

The effectiveness of an e-learning environment mainly encompasses on how efficiently the tutor presents the learning content to the candidate based on their learning capability. It is therefore inevitable for the teaching community to understand the learning style of their students and to cater for the needs of their students. One such system that can cater to the needs of the students is the Intelligent Tutoring System (ITS). To overcome the challenges faced by the teachers and to cater to the needs of their students, e-learning experts in recent times have focused in Intelligent Tutoring System (ITS). There is sufficient literature that suggested that meaningful, constructive and adaptive feedback is the essential feature of ITSs, and it is such feedback that helps students achieve strong learning gains. At the same time, in an ITS, it is the student model that plays a main role in planning the training path, supplying feedback information to the pedagogical module of the system. Added to it, the student model is the preliminary component, which stores the information to the specific individual learner. In this study, Multiple-choice questions (MCQs) was administered to capture the student ability with respect to three levels of difficulty, namely, low, medium and high in Physics domain to train the neural network. Further, neural network and psychometric analysis were used for understanding the student characteristic and determining the student's classification with respect to their ability. Thus, this study focused on developing a student model by using the Multiple-Choice Questions (MCQ) for integrating it with an ITS by applying the neural network and psychometric analysis. The findings of this research showed that even though the linear regression between real test scores and that of the Final exam scores were marginally weak (37%), still the success of the student classification to the extent of 80 percent (79.8%) makes this student model a good fit for clustering students in groups according to their common characteristics. This finding is in line with that of the findings discussed in the literature review of this study. Further, the outcome of this research is most likely to generate a new dimension for cluster based student modelling approaches for an online learning environment that uses aptitude tests (MCQ's) for learners using ITS. The use of psychometric analysis and neural network for student classification makes this study unique towards the development of a new student model for ITS in supporting online learning. Therefore, the student model developed in this study seems to be a good model fit for all those who wish to infuse aptitude test based student modelling approach in an ITS system for an online learning environment.

Keywords: Intelligent Tutoring System, Multiple Choice Question, Online Learning Environment, Student Model, Neural Network

PEMBANGUNAN MODEL PELAJAR BAGI SISTEM PENUTORAN PINTAR

ABSTRAK

Tahap keberkesanan sesuatu sistem e-pembelajaran adalah sangat bergantung kepada kecekapan pengajar dalam membentangkan kandungan pembelajaran kepada pelajar berdasarkan tahap pembelajaran pelajar. Justeru, adalah penting bagi komuniti tenaga pengajar untuk memahami gaya pembelajaran pelajar dan memenuhi keperluan pelajar. Salah satu sistem bagi memenuhi keperluan pelajar adalah Sistem Penutoran Pintar atau Intelligent Tutoring System (ITS). Bagi mengatasi cabaran-cabaran yang dihadapi oleh pengajar untuk memenuhi keperluan pelajar, pakar-pakar e-pembelajaran dewasa ini telah memberikan tumpuan terhadap ITS. Banyak kajian lepas telah mencadangkan yang maklumbalas yang bermakna, berkonstruktif dan beradaptif adalah cirri-ciri penting ITS dan maklumbalas inilah yang membantu pelajar mencapai pembelajaran yang kukuh. Pada masa yang sama, model pelajar memainkan peranan penting dalam merancang laluan latihan, memberikan malumat maklumbalas kepada modul pedagogi dalam sistem tersebut. Model pelajar juga menyimpan maklumat spesifik tentang pelajar. Kajian ini telah menggunakan soalan-soalan objektif (MCQ) yang bertujuan untuk mengukur kebolehan pelajar berdasarkan tiga tahap kesukaran dalam bidang Fizik iaitu rendah, medium dan tinggi untuk melatih rangkaian neural. Lanjutan daripada itu, rangkaian neural dan analisis psikometrik telah digunakan bagi memahami ciri-ciri pelajar dan menentukan klasifikasi pelajar berdasarkan kebolehan mereka. Kajian ini menumpukan dalam membina model pelajar menggunakan soalan-soalan objektif (MCQ) bagi integrasi ke ITS dengan menggunakan rangkaian neural dan analisis psikometrik. Walaupun regresi linear di antara ujian sebenar dan peperiksaan akhir adalah lemah iaitu sebanyak 37%, namun hasil kajian ini menunjukkan kejayaan dalam mengklasifikasi pelajar sehinggan 80 peratus (79.8%) menjadikan model pelajar ini sesuai mengklusterkan pelajar kepada kumpulan berdasarkan ciri-ciri umum mereka. Hasil kajian ini adalah sejajar dengan hasil kajian yang dibincangkan dalam bahagian kajian kesusasteraan. Hasil kajian ini juga berkemungkinan untuk memberi perspektif baru dalam pemodelan pelajar berdasarkan cluster untuk pembelajaran atas talian yang menggunakan ujian aptitud (MCQ) terhadap pelajar-pelajar yang menggunakan ITS. Penggunaan analisis psikometrik dan rangkaian neural dalam mengklasifikasikan pelajar menjadikan kajian ini unik dalam membangunkan model pelajar bagi ITS untuk menyolong pembelajaran atas talian. Oleh itu, model pelajar yang yang dibangunkan dalam kajian ini adalah sesuai untuk sesiapa sahaja yang ingin menggunakan ujian aptitud dalam permodelan pelajar untuk sistem ITS.

Kata kunci: Intelligent Tutoring System, Multiple Choice Question, Pembelajaran Online, Model Pelajar, Rangkaian Neural

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
AT	Adaptive Tutorials
ALS	Adaptive Learning System
BPN	Back-Propagation Network
FNN	Feed Forward Neural Network
GSM	General Student Model
IRT	Item Response Theory
ITS	Intelligent Tutoring System
MCQ	Multiple Choice Question
OCR	Optical Character Reader
OLE	Online Learning Environment
PCA	Principal Components Analysis
WBLT	Web-based Learning Tools

Chapter 1

General Introduction

1.1 Introduction

Ever since the computers were invented, they were often compared with a human brain or considered to mimic its intelligence. However, the main difference between them is the unique reasoning ability of the human brain. That is, for example, if we learn to play the piano over several months, the structure of our brain changes. Similarly, in the case of tutoring the students, a process referred as an Intelligent Tutoring System (ITS) is used to train a system by capturing the students' learning behavior to provide a direct modified tutoring or a response to the students. ITS keeps track of the progress of a student through logs generated during a session, and provides visual feedback on the student's progress through the editor and interface (Chaachoua et al., 2004, Lagud, Rodrigo, 2010). Many ITS authoring systems have been developed since the earliest days of preparing an Intelligent Tutoring System (Murray, 2003). However, each authoring tool focuses on a kind of ITS, such as constraint-based tutors (Mitrovic et al., 2009) or model-tracing tutors (Blessing, Gilbert, Ourada & Ritter, 2007). Although many rapid prototypes of ITSs have been used in the past, there have been a lot of challenges among the pedagogical community to find an appropriate tutoring system. This is because there have been a variety of objectives behind ITS authoring systems, which comprise of four sub systems or modules, such as: the interface module, the expert module, the student module and the tutor module. According to Woolf, (2009),in an ITS, the student model stores information that is specific to each individual learner: it concerns “how” and “what” the student learns or his/her errors, and the student model plays a main role in planning the training path, thereby supplying information to the pedagogical module of the system. This component provides a pattern of the educational process by using the student model to decide the instruction method that reflects the different needs of each student. Therefore, this study is an attempt in developing a student model by congregating the learning patterns of each individual student by providing a Web based user interface with a MCQ-based feedback system for integrating it with an Intelligent Tutoring System.

1.2 Background

In an online learning system, pedagogical strategies are important as it links ICT with innovative approaches. This is also quoted in the book titled ‘The Pedagogy Strategy' MCEETYA. (2005), as follows:

“Pedagogies that integrate information and communication technologies can engage students in ways not previously possible, enhance achievement, create new learning possibilities and extend interaction with local and global communities” (p.2).

According to (Lankshear & Bigum, 2003), the students who having grown up with new technology are not only comfortable in cyberspace but also in tune with it; being largely at ease with the dizzy pace of change due to the development of new technologies and social and economic shifts. These new clients work in different ways with technology and have different mindsets, a term evident in Lankshear's work (Lankshear & Bigum, 2003b; 2003c). These digital mindsets are different from those held by the educators who are controlling how technologies are used in schools. Added to it, the professional development of ICT is perceived as an avenue for pedagogical change based on the notion that its implementation will signify subtle shifts in expectations of schooling in the 21st century and that alternate modes of using ICT in classrooms can be modeled with deliberate approaches within professional development programs (Phelps, Graham & Kerr, 2004).With increased technology, gadgets such as, iPad, *iPhone*, Tablets etc., are in use by the students, thus enabling the educators to make the learning environment interesting. Now, as we move toward a digital society, students are exposed to technology and digital devices that keep them engaged. Therefore, when they come to school, they have little or no patience for receiving information through a lecture-style teaching. Students are seeking a high-tech, digital experience in the classroom. It is the same with the online learners, who want to learn in their own way and at their own flexible timings. This is one of the reasons why Web-based Lecture Technologies (WBLT) have been popular in online teaching. The use of WBLT are also equally gaining in popularity among students, since they are realizing that their needs for flexibility are not being met by 'traditional on campus teaching paradigms'(Lefoe & Albury, 2004). With increased demands posed by work and family commitments (Anderson, 2006; McInnis & Hartley, 2002), previous studies have confirmed students' appreciation of the convenience and flexibility offered by 'anytime, anywhere access to lectures' (Fardon, 2003; McNeill, Woo, Gosper, Phillips, Preston & Green, 2007; Williams & Fardon, 2007). Similar results are also emerging from studies, which use data from usage logs for specific web-based lecture technologies (Von Konsky, Ivins & Gribble, 2009).

In addition to flexibility, students are usually positive about the impact these technologies have on their learning (Williams & Fardon, 2005; Woo, Gosper, McNeill, Preston, Green & Phillips, 2008). More studies (McElroy & Blount, 2006; Soong, Chan, Cheers & Hu, 2006) found students agreeing that recordings of lectures enhanced the course they were learning, when compared to other courses without this facility. Additionally, there is evidence that students use WBLT as a study tool to complement face-to-face lectures (Signor, 2003; Williams & Fardon, 2007). Students reported using WBLT to support their learning by checking lecture notes, by reviewing difficult concepts, by revising for exams and by listening to missed lectures (McElroy & Blount, 2006). Thus, as suggested by Craig, Wozniak, Hyde & Burn (2009), distinct and diverse patterns of student-usage are emerging. The response to WBLT by academic teaching staff has been less consistent than by their student counterparts. Some lecturers have adopted WBLT as tools, which can be used to enhance the learning by a student and the flexibility in the learning process (Williams & Fardon, 2007) while other lecturers have criticised WBLT as reinforcing lecturing as a primary learning activity (Donnan, Kiley& McCormack, 2004) or contributing to students' low attendance (Williams & Fardon, 2007; Phillips, Gosper, McNeill, Woo, Preston & Green, 2007). Academics have acknowledged the equity advantages inherent in the adoption of WBLT (Chang, 2007). However, staffs have simultaneously reported lower ratings for both 'satisfaction' and 'importance for online learning environments', generally (Palmer & Holt, 2009). It has always been a challenging task to build Web-based Lecture Technologies, which best suits the pedagogical community. This is because, students' knowledge of understanding differs from student to student and to design a learning environment that best suits them is a very challenging task. To overcome this issue, e-learning experts in recent times have focused on developing Intelligent Tutoring Systems (ITS). In recent years, the paradigm has begun to shift and researchers have started to explore ITSs that support collaborative learning. The field of Computer Supported Collaborative Learning (CSCL) explores how students learn in collaborative settings and how technology can support this collaboration (Harsley, 2015). The reason being, Intelligent Tutoring Systems allow learners to hone their abilities by completing assignments within interactive academic settings. ITS can answer questions and provide personalized assistance to the learner. ITS, unlike other educational technologies, evaluate every student's response in order to assess his/her knowledge and skills (Ong & Ramachandran, 2000). ITS can then modify instructional strategies, give explanations, examples, demonstrations, and practice exercises where necessary (Ong & Ramachandran, 2000). ITS offer more options in the presentation of material and have the capability to specialize information to cater to a student's needs (Beck, Stern, & Haugsjaa, 2004). Researchers often tend to use many terms to explain computer aided instructions. However, (Wenger, 1987) some researches prefer to use Adaptive Tutoring Systems or Flexible Tutoring Systems. In fact, all these terms try to reflect the personalized tutoring that uses AI and adapt to the context of the instruction. The main role of an Intelligent Tutoring System (ITS) is to provide assistance during the instructional process that is deployed to the learner. In fact, all these terms try to reflect the personalized tutoring that uses AI and adapt to the context of the learning process (Moise, 2007). However, in this study the focus is only on ITS and its components that intend todeliver instructions to the students. In the next section, the constituents of an ITS and the role of each module within it are explained.

1.2.1 Intelligent Tutoring System and its Components

An ITS focuses education as a process of cooperation between tutor and student in which the tutor tries to teach concepts to the student. The tutor has to determine and apply more appropriate teaching strategies at every moment (Case., Porter., Gyi ., Marshall ., & Oliver, 2001). These questions are what to explain, what detail level is necessary, when and how to interrupt the student and how to detect and to correct errors. The four basic components that classically are identified in an ITS are: Domain Module, Pedagogical Module, Student Module, Dialogue Module (Case., Porter., Gyi ., Marshall ., & Oliver, 2001; Yazdani, 2001). However, according to Htaik and Amnuaisuk (2003), these four basic components are viewed as the interface module, the expert module, the student module, and the tutor module (Htaik, T.T., & Amnuaisuk, P.S., 2003). Traditional ITSs contains complex student model, which involves expert systems, knowledge tracing and bug diagnosis have proven difficult, complex and costly to develop. However, student model does not necessarily have to be this complex to prove effective. Simple student model that provide information on individual learners can be useful. In fact, student modelling has diversified substantially to include other types of artificial intelligence such as reinforcement learning, neural networks, and bayesian networks (Smith, 2007).

1.2.2 Student Model and its Significance in an ITS

Student models have also become a part of other types of learning technologies, such as intelligent learning environment, which combine aspects of Intelligent Tutoring System with one or more open-ended learning environments, and adaptive hypermedia, which adapts websites to the needs of individual users. Adaptive Tutorials (ATs) are web-based eLearning modules where an Intelligent Tutoring System (ITS) adapts the instruction level (difficulty, feedback and activity-sequence) to that of the learners', based on their individual performance. From a pedagogical point of view, ATs are similar to teaching laboratory activities and are analogous to the concept of tutorial simulations as described by Laurillard (2002). Additionally, the growing field of user-modeling also studies adaptations of computer systems for individual users (Kobsa, 2001). Added to this, the most critical component of ITS is the student module whose necessity has been addressed by (Jeremic & Devedzic, 2004) as follows: Simply, this module is about the theory of behaviours of a student, and it generates all information about the individual learner. The student model evaluates each learner's performance to determine his or her knowledge, perceptual abilities and reasoning skills. It provides the information such as what the student knows or does not know, any misconceptions and student's degree of forgetfulness (Jeremic & Devedzic, 2004).

VanLehn (2005), in the Air Force Research Laboratory presents the following simple example of a hypothetical arithmetic tutoring system. Imagine that three learners are presented with addition problems that they answer as follows:

Table 1.1

ITS – Student Modeling Example Source: (VanLehn et al., 2005.)

Student A	22	46
	+39	+37
	51	73
Student B	22	46
	+39	+37
	161	183
Student C	22	46
	+ 39	+37
	62	85

Though all three participants answered incorrectly, different underlying misconceptions caused each person's errors. Student A fails to carry, Student B always carries (sometimes unnecessarily) and Student C has trouble with single-digit addition. In this example, the student supplies an answer to the problem, and the tutoring system infers the student's misconceptions from this answer. By maintaining and referring to a detailed model of each user's strengths and weaknesses, the ITS can provide highly specific, relevant instruction (Jim & Sowmya, 2000). The General Student Model (GSM) framework consists of a database, for the storage of student information and meta-data on the structure of the student information; a web service; to allow learning environments to dynamically retrieve and update student information; a programming interface, for the interaction between the GSM and the individual learning environment; and a web interface, to allow researchers to specify the form of student data that will be stored (Smith, 2007). Thus, student models, in some form, will remain a valuable part of a variety of types of computer-based learning environments available for knowledge assessment.

1.2.3 Conclusion

In today's digital world, there is a paradigm shift in theories on online pedagogy. This is because teachers find multiple ways to engage students. At the same time, there is large amount of information that students need to learn in shorter spans of time as they also look forward for various learning tools to get engaged. For an Online-learning environment, the Intelligent Tutoring System offers more options in the presentation of material and has the capability to specialize information to cater to a student's needs (Beck, Stern, & Haugsjaa, 2004). However, with enormous innovations in technology and multiple channels in which student can be engaged, there is certainly a wide scope for developing supportive theories and strategies that are needed for developing various components within an Intelligent Tutoring System.

1.3 Significance and usefulness of this research study

Concepts from AI, such as, neural networks were used by many researchers for predictions of students' results. For example, Cooper, (2010) presents a neural network-based decision support system that identifies students who are "at-risk" of not retaining their second year of study. The system correctly predicted retention for approximately 70% of the students. Halachev, (2012) presents a neural network used for the prediction of the outcome indicators of e-Learning, based on a Balanced Scorecard. Neural networks can bring psychometric and econometric approaches to the measurement of attitudes and perceptions (Davies, Luiz & Bruce, 1996). Many researchers tried to predict the students' results based on various data. Predictions were made using different statistical methods like multivariate regression, path analysis or discriminant analysis. None of these methods have the power of discovering potential data patterns as neural networks. Feed forward neural networks are applied in many fields like financial forecasting, medical diagnosis, bankruptcy prediction and OCR for regression or classification purposes because they are one of the best functional mappers. The good results of applying neural networks in classification problems lead to their usage for predicting students' results in higher education (Bogdan, Raluca & Stefan, 2013). In this study, neural network and psychometric analysis are used to classify the students and store the student's knowledge in the form of a student profile or log file. This process of classification of students makes this study a unique one. Added to it, according to education Bogdan, Raluca & Stefan, (2013), most of the systems developed have only shown a correct predicted retention for approximately 70% of the students. This study may also be a channel for finding if the correct predicted retention of the students exceeds this percentage during the student modeling classification process.

Added to the above significance of this study, researchers, such as Rane and Sasikumar (2007) pointed out that to overcome the lack of the presence of a teacher, intelligent tutoring systems attempt to simulate a teacher, who can guide the student's study based on the student's level of knowledge by giving intelligent instructional feedback. In addition, in Gheorghiu's and Van Lehn's (2008) paper, they have also suggested that meaningful, constructive and adaptive feedback is the essential feature of ITSs and it is such feedback that helps students achieve strong learning gains.

Thus, we see that learning activities rely on a feedback mechanism, which is an essential feature of ITSs. Further, researchers investigating the effect of different types of feedback in web-based assessments showed positive results using MCQs in online test for formative assessment (e.g. Payne et al. 2007; Guo, Palmer-Brown, Lee, & Cai, 2014). Hence, this study is an attempt to provide a new knowledge to all those who intend to build a MCQ based Intelligent Tutoring System by developing an ideal Student Model.

From the above significance emerges the following usefulness of this study:

Intelligence of a Web-based Educational System is the capability of demonstrating some form of knowledge-based reasoning in curriculum sequencing, in analysis of the student's solutions and in providing interactive problem-solving support (possibly example-based) to the student; all of which are adapted to the Web technology (Brusilovsky & Miller, 2001). Thus, the usefulness of this research study is an attempt to develop a student model that can play an important role in building an Integrated Tutoring System (ITS) for:

- Collecting some data about the student working with the system, thereby creating the student model.
- Adapting the presentation of the course material, navigating through it, sequencing it, and annotating it, for the student.
- Using models of different students to form a matching group of students for different kinds of collaboration.
- Identifying the students who have learning records essentially different from those of their peers (e.g., the students scoring too low or too high and acting accordingly).

(e.g., show additional explanations or present more advanced material).

Further this study encapsulates within the four domains of an ITS system and gives an inference to some of the key points that could be very useful. For example,

1) What key components need to be used in the current student model?
2) How can a student profile be efficiently generated?
3) How to identify the students' learning behavior patterns?
4) Can tools such as Artificial Neural Network (ANN), psychometric analysis and Item Response Theory be useful for the current system under development?

1.3.1 Novelty of the research

This research is an attempt to contribute towards the development of a framework for an ideal students' learning style by developing a student model. As such, this research attempts to provide a theoretical coherence by providing a common approach for an Intelligent Tutoring System environment. Since, this research uses Neural Networks for identifying students' learning pattern and Psychometric Analytical Techniques for categorizing them by providing a suitable learning content, this research, ideally, is a contribution towards curriculum sequencing. For instructional developers, this research would serve as a heutagogical approach towards teaching and learning, whereby, learners become highly autonomous and self-determined. This is because, this research provides the emerging learners a heutagogical learning environment, as it facilitates development of capable learners and emphasizes both on the development of the learner competencies as well as the development of the learner's capability and capacity to learn (Ashton & Newman, 2006; Bhoryrub, Hurley, Neilson, Ramsay, & Smith, 2010; Hase & Kenyon, 2000). Further, the outcome of the research is most likely to generate a framework for web-based learning environment for the MCQ-based ITS learners. As such, this approach can also serve as a theory for applying to emerging technologies in distance education and for guiding distance education practice and the ways in which distance educators develop and deliver instruction using newer technologies, such as, Intelligent Tutoring System.

1.4 Problem statement

The success of an e-learning environment mainly encompasses on how efficiently the tutor presents the learning materials to the candidates based on their learning capability. What is needed in order to assist the students in their learning process is the requirement of a back-up knowledge about the candidates and how the content interplays between the candidates and the system in the guiding process. Therefore, there is a developing demand for adapting learning material such as, lessons, exercises, tests for each individual. Further, as pointed by Coffield, et.al.,(2004), “just varying delivery style may not be enough and the unit of analysis must be the individual rather than the group”. That is, when we analyze a group, the findings often suggest that learning styles are relatively unimportant, however, when we analyze an individual, then the learning style often distinguishes itself as a key component of being able to learn or not. Thus, those who are actually responsible for helping others to learn; such as, teachers, instructional developers or trainers often see these learning styles and the need for adjusting them according to the preference of the individual. Hence, there is a very serious need for providing an appropriate learning environment for the pedagogical community, with a learning method that best suits them. Intelligent Tutoring System (ITS), is one such instructional process that provides personalized tutoring to the learners, which uses AI and adapt to the context of learning process (Moise, 2007). However, such ITSs comprises of four modules, namely: Domain Module, Pedagogic Module, Student Model and Dialogue Module (Case., Porter., Gyi., Marshall., & Oliver, 2001 Yazdani, 2001). The Student Model plays an important role among these four modules in creating an effective student profile for serving appropriate learning contents to the students based on their ability, skill and knowledge. In this study, an attempt has been made to enhance the Student Modelling in a way wherein it can present the learning materials for the candidates based on the recent trends. This component provides a pattern of the educational process by using the student model to decide the instruction method that reflects the different needs of each student. Therefore, this study is an attempt in developing a student model by congregating the learning patterns of each individual student by providing a Web based user interface with a MCQ-based feedback system for integrating it with an Intelligent Tutoring System. Additionally, there has not been much research on a complete Student Model for a Multiple Choice Question based Intelligent Tutoring System. According to Blessing et al.(2007), the intense interaction and feedback achieved by Intelligent Tutoring Systems can significantly improve the learning gains of a student. In addition, in Gheorghiu's and VanLehn's (2008) paper, they have also suggested that meaningful, constructive and adaptive feedback is the essential feature of ITSs and it is such feedback that helps students achieve strong learning gains. Thus, we see that learning activities rely as an embodiment for successful implementation of an Intelligent Tutoring System. Further, researchers investigating the effect of different types of feedback in web-based assessments showed positive results using MCQs in online tests for formative assessments(e.g. Epsteinet al. 2002; Higgins and Tatham 2003; Kuechler and Simkin 2003; Payne et al.2007). Springgay and Clarke (2007) suggested including examples of feedback to achieve better perception of feedback. Multiple Choice Questions (MCQs) are an effective way to provide students with a feedback. The use of MCQs has been widely studied. A number of advantages can be found in the study by Epstein et al. (2002), Higgins and Tatham (2003) and Kuechler and Simkin (2003). However, there is lack of research of such Multiple Choice Questions (MCQs) being used in Student Modelling-process for integrating with an MCQ-based ITSs. Therefore, it is only with this intention that this research is carried out for the pedagogical community across the higher educational institutions, who intend to deliver the learning content though Interactive Tutoring System (ITS).

1.5 Research Aim and Objective

This study aims in developing a suitable Student Model for a web-based Intelligent Tutoring System (ITS) that is intended to provide independent learning for the pedagogical community with a Multiple-Choice Question-based Learning environment.

Further, the students' learning behavior will also be analysed using Neural Network Techniques and Psychometric Tests based on their learning and ability.

The main objectives of this study are:

1) To create a Web-based user interface for creating learning content (MCQ) for designing a student model.
2) Attempt to provide suitable learning materials based on the student's ability and skills.
3) Analyse the students' learning behaviour using neural network schema.
4) Identify the most preferred learning pattern by classifying them using psychometric analysis technique.
5) To provide a framework for designing a Student Model for a pedagogical interface with a MCQ-based feedback for integrating it with an Intelligent Tutoring System.

1.6 Research Questions

The following are the research questions:

RQ1: Is there a significance between the practice test scores and the real test scores after the neural network intervention?

Based on the above question we have the following research and statistical hypotheses:

Research hypotheses: There is a significant difference between the practice test scores as against the real test scores after the neural network intervention.

Formally, a statistical hypothesis-testing problem includes two hypotheses. The hypothesis are referred to as the null (H_0) and the alternative hypothesis (H_1). Although we would like to directly test research hypothesis, we actually test the null. If we disprove the null, then we indirectly support the research hypothesis since it competes directly with the null.

Statistical hypotheses:

H_0: There is no significant difference among the practice test scores and the real test scores after the neural network interception.

H_1: There is a significant difference among the practice test scores and the real test scores after the neural network interception.

RQ2: Is there a correlation between the real test scores obtained after neural network interception and the Final exam marks?

Based on the above question we have the following research and statistical hypotheses:

Research hypotheses: There is a significant difference among the real test scores obtained after neural network interception and the Final exam marks.

Statistical hypotheses:

H_0: There is no significant difference among the real test scores obtained from the neural network intervention and the Final exam marks.

H_1: There is a significant difference among the real test scores obtained from the neural network intervention and the Final exam marks.

RQ3: How far the practical test scores obtained before the neural network interception best fit psychometrically?

RQ4: Does the pattern of the practice test scores and real test score show a good fit for a linear model in order to classify the students?

RQ5: How far the student's classification ideally fit into the final students predicted level and obtained level during the process of designing the Student Model?

1.7 Academic contribution of the research

With a confused mindset of pedagogical experts in bringing novelty to their teaching, using Web-based Lecture Technologies in pedagogy (WBLT), it has always been a challenging task to design a learning environment that best suits them. One such area which has been largely thought off in the recent times is the Intelligent Tutoring System (ITS). The main feature of this kind of tutoring system is the adaptation to the users need (Gunderson,1994, Myers,1995). Such an ITS normally consists of four domains, namely, Interface Module, Expert Module, Student Module and Tutor Module. It is the Student Module that holds the information, which is specific to each individual learner. It concerns "how" and "what" the student learns or his/her errors, and the Student Model plays a main role in planning the training path, supplying information to the pedagogical module of the system (Woolf, 2009). The more a system knows about users the better it can serve them effectively. But there are different styles and even philosophies, to teach the computer about user habits, interests, patterns and preference. For example, performance measures are a simple way to describe a student. It is computationally simple to measure the student's answers and carry out some statistical aggregation procedures. It is a global representation of the student; it can only support global actions on the part of the tutor; for example, upgrading or downgrading the difficulty of practice items. But it does not provide the level of detail necessary to decide what this student needs right now in order to learn a particular concept, procedure, fact or principle.

Therefore, this research is an attempt for developing a student model based on MCQs-based feedback system for incorporating it within ITS system.

1.8 Theoretical framework of this research

Theoretical framework is a conceptual model of how one theorizes or makes logical sense of the relationships among several factors that have been identified as important to the problem (Sekaran, 2000). Therefore, it is important to deduce the theoretical framework for this study, before conceptualizing this study.

It has always been a challenging task to build Web-based Lecture Technologies, which best suits the teaching and learning community. This is because, student's knowledge of understanding differs from one student to another and to design a learning environment that best suits them is a very challenging task (Ong & Ramachandran, 2000). To overcome this issue, e-Learning experts in recent times have focused on Intelligent Tutoring System (ITS). The reason being, Intelligent Tutoring Systems allow learners to hone their abilities by completing assignments within interactive academic settings. ITS can answer questions and provide personalized assistance to the learner. ITS, unlike other educational technologies, evaluate every student’s response in order to assess his/her knowledge and skills. ITS can then modify instructional strategies, give explanations, examples, demonstrations, and practice exercises wherever necessary (Ong & Ramachandran, 2000). ITS offer more options in the presentation of material and have the capability to specialize information to cater to a student's needs (Beck, Stern, & Haugsjaa, 2004).

The most critical component of ITS is the student module whose necessity has been addressed by (Jeremic & Devedzic, 2004) as follows: Simply, this module is about the theory of student behaviours and it generates all information about an individual learner. The student model evaluates each learner’s performance to determine his or her knowledge, perceptual abilities and reasoning skills (Jim & Sowmya, 2000).

In this study, the development of a Student Model is completely on an online environment. For an online learning environment, there are theories on online pedagogy, namely, instructive approach and constructive approach. Lucas (2005), states that the instructive approach incorporates a teacher-directed and carefully planned curriculum, with purposeful teaching at its core. On the other hand, constructivist learning focuses on students' active participation in problem-solving and critical thinking regarding a learning activity, which they find relevant and engaging. Learners are constructing their own knowledge by testing ideas and approaches based on their prior knowledge and experience; applying these to a new situation and integrating the new knowledge gained with pre-existing intellectual constructs. Since in this study, learners are not teacher-directed, our focus will be on constructivist learning. Further, pedagogical models grounded in situated cognition and constructivist learning includes promoting or supporting authentic learning activities. This authentic learning in turn can rely on educational software developed to stimulate typical scenarios that professionals encounter in real-world settings. Along with communication tools, these online experiences often integrate ITS, concept mapping, immediate feedback and opportunities for reflection; including the chance to replay recorded events and adopt alternative decision paths (Ferry et al, 2004).

Rane and Sasikumar (2007) pointed out that to overcome the lack of the presence of a teacher, Intelligent Tutoring Systems attempt to simulate a teacher who can guide the student's study based on the student's level of knowledge by giving intelligent instructional feedback. In addition, in Gheorghiu's and Van Lehn's (2008) paper, they also suggested that meaningful, constructive and adaptive feedback is the essential feature of ITS and it is such feedback that helps students achieve strong learning gains.

Thus, we see learning activities rely on tools such as Intelligent Tutoring System. Further, researchers investigating the effect of different types of feedback in web-based assessments showed positive results using MCQs in online tests for formative assessment (e.g. Epstein et al. 2002; Higgins and Tatham 2003; Kuechler and Simkin 2003; Payne et al.2007). Thus the theoretical framework underpinning this study is depicted in the Figure 1.1.

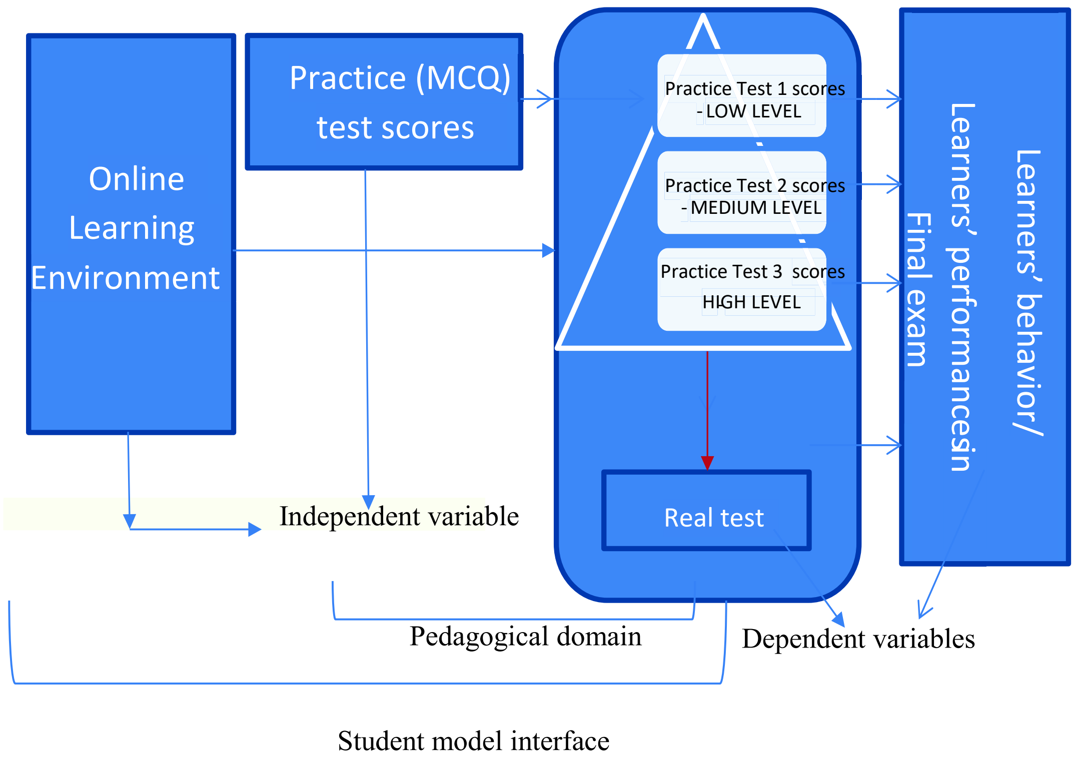

Figure 1.1: Theoretical framework of the research

1.9 Conceptual framework of the study

According to Miles and Huberman (1994, p-18), "conceptual framework explains graphically or by narration, the main things to be studied – the key factors, concepts and variables – and the presumed relationship among them". Added to this he states "it is the researcher's own position on the problem – the way the researcher shapes it together. A clear statement of the research problem is often not justifiable until the conceptual framework is developed". The conceptual framework of this study emerges from the three schools of thought namely, behaviourism, cognitive psychology and constructivism. These have been widely used and explored to provide guidance for instructional practice: behaviourism, cognitive psychology and constructivism (Villalba, Romiszowski, 2001). However of the three, constructivism has been identified as the most suitable one for online learning environments (Hung 2001, Oliver 1999, Hung & Nichani 2001). In the case of Intelligent Tutoring System (ITS), instructional strategies are tailored in terms of content and style, providing explanations, hints, examples, demonstrations and practice problems as needed (Jim & Sowmya, 2000). However, according to Dabbah (2005), the first key component of the theory-based design framework for e-Learning is the Pedagogical Models. Pedagogical Models lead to the specification of instructional strategies, which is the second key component of the theory-based design framework for e-Learning (Dabbah, 2005). Since in this study, the Student Model is designed to engage online learners, the main theory underlying this conceptual framework is based on constructivism. This is because the constructivist view of learning emphasizes students' active involvement in the learning activities, collaboration among them and students' interactions with a variety of information resources; to construct meaning through experimentation, acquisition of empirical experience and appropriate pedagogical guidance.

1.9.1 Link between Student Model and Pedagogical Model

Pedagogical Models are cognitive models or theoretical constructs derived from knowledge acquisition models or views about cognition and knowledge, which form the basis for the learning theory. In other words, they form the mechanism by which we link theory to practice. In the case of ITS, it is the Pedagogical Module that contains the knowledge of how to teach, that is, a teaching or tutoring strategy and orchestrates the whole tutoring process. The Pedagogical Module in turn uses information from the Student Model to determine what aspects of the domain knowledge should be presented to the learners. Thus we see that an interaction exists between the Student Model and Pedagogical Model in sharing information that is needed to serve the learning content based on the learners' knowledge. In ITS, the cognitive modeling has long been an integral part and is the activity of producing a detailed and precise description of the knowledge involved in student performance in a given task domain (Clark et al. 2007). Two types of cognitive models that are used frequently in ITS are the rule-based models (Crowley and Medvedeva 2006; Butcher & Aleven 2007; Van Lehn et al. 2005) and constraint-based models (Mitrovic et al. 2001). While, rule-based models capture the knowledge involved in generating the solution step-by-step, constraint-based models express the requirements that all solutions should satisfy. Both types of models have been used successfully in real-world ITS (Aleven et al. 2006; Mitrovic et al. 2009). Added to it, constraint-based modeling is a student modeling method that describes only pedagogical informative states, rather than following the procedures that students used to arrive at their answers (Ohlsson, 1994). Thus in this study, as the rule-based models are not used, the focus is on constraint-based model.

One of the central components of Intelligent Tutoring Systems is the Student Model, which is a qualitative representation that accounts for student behaviour in terms of existing background knowledge and represents the system's belief about the learner's knowledge (Stauffer, 1996). It comprises of two distinct forms of knowledge: the domain theory and the bug library (Sison & Shimura, 1996b). The domain theory corresponds to the ideal model of students' behaviour and in some cases it is completely specified. Since, a student's behavior is any observable response that is used as input to the student modeling process (Sison & Shimura, 1996b), the domain theory is important in the construction of student modeling.

Researchers in student modeling areas have used AI techniques in order to develop models that provide detailed diagnosis of student's knowledge, bugs and misconceptions, and/or simulate the cognitive behaviour of a student during learning and problem solving activities (Greer & McCalla, 1994). At the same time, concepts from AI, such as Neural Networks were used by many researchers for predictions of students' results. For example, Cooper, (2010) the author, presents a neural network-based decision support system that identifies students who are "at-risk" of not retaining till their second year of study. The system correctly predicted retention for approximately 70% of the students. Halachev, (2012) presents a Neural Network used for the prediction of the outcome indicators of e-Learning, based on Balanced Scorecard (More examples were discussed in Literature review of this study).

Neural Networks can bring psychometric and econometric approaches to the measurement of attitudes and perceptions (Davies, Luiz & Bruce, 1996). Many researchers tried to predict the students' results based on various data. Predictions were made using different statistical methods like multivariate regression, path analysis or discriminant analysis. None of these methods have the power of discovering potential data patterns as Neural Networks. Feed Forward Neural Networks are applied in many fields like financial forecasting, medical diagnosis, bankruptcy prediction, OCR for regression or classification purposes because they are one of the best functional mappers. The good results of applying Neural Networks in classification problems lead us to use them for predicting students' results in higher education (Bogdan, Raluca & Stefan, 2013). Thus in this study, Neural Network concepts are used to classify the students and store the student's knowledge in the form of a student profile log in the database. The conceptual framework for this study is illustrated in Figure 1.2.

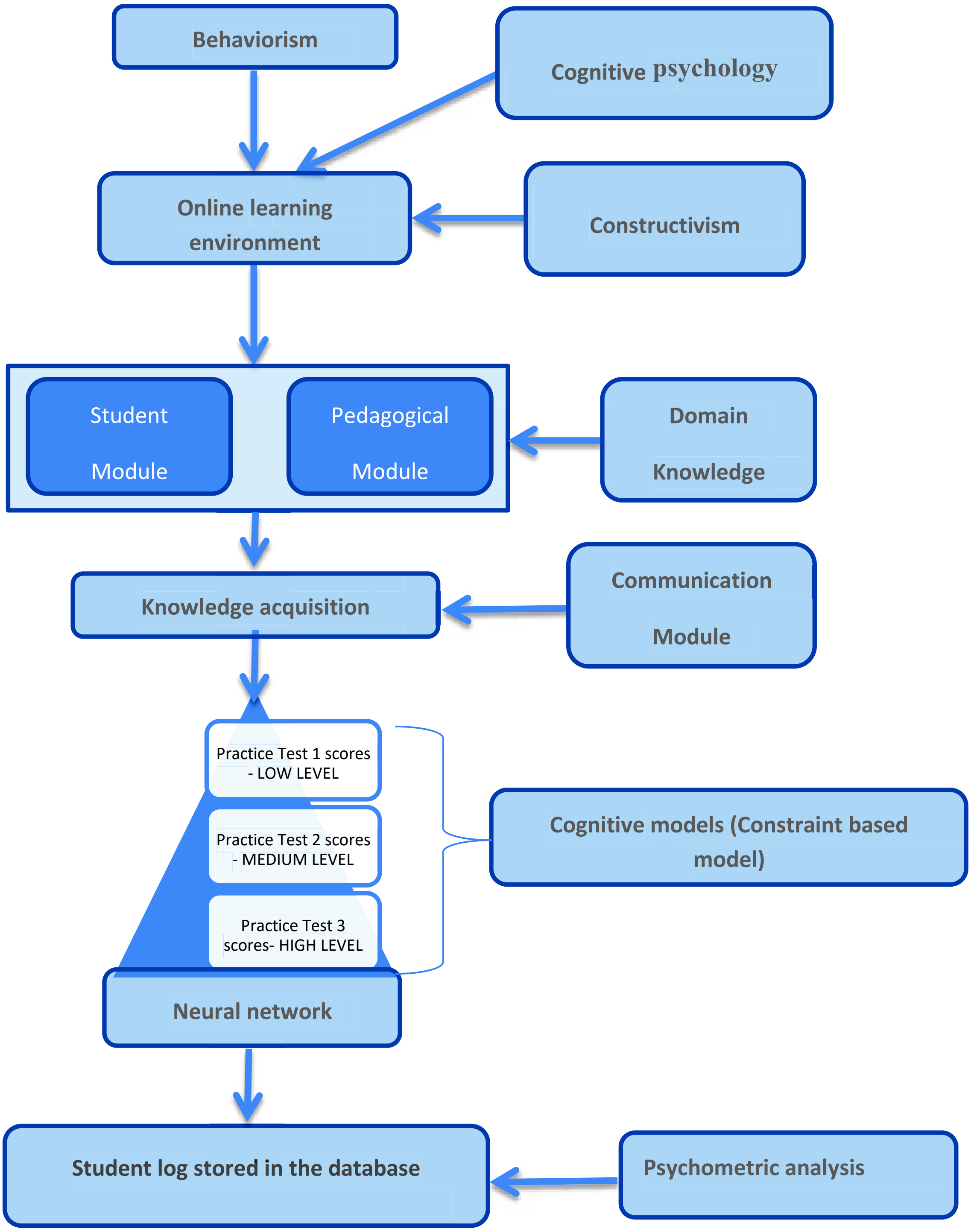

Figure 1.2: Conceptual framework of the study

1.10 Limitations of this study

1) Both ITS and AH are normally used for computer-based instruction. However, adaptive hypermedia is better suited for the instruction of concepts, while Intelligent Tutoring System generally assists in the use of these concepts to solve problems. In general, an instruction system requires both of these instructional approaches in order to provide a full learning environment (Phobun & Vicheanpanya, 2010). However, for this research study, the focus will only be on Student Model of ITS, as its goal is to provide one-to-one instructions by providing learners to carryout tasks in a highly interactive learning environment.

2) Normally, computer based systems such as CAL (Computer Aided Learning) or CBT (Computer Based Training) use traditional instructional methods by providing instruction to learners without concerning themselves with a model of the learner's knowledge. Thus, these instructions sometimes cannot assist learners individually. By contrast an ITS assesses each learner's actions within these interactive environments and develops a model of their knowledge, skills, and expertise. Based on the learner model, it can tailor instructional strategies, in terms of both the content and style and provides relevant explanations, hints, examples, demonstrations and practice problems to individual learner. Therefore, in this study, the focus will only be on Student Model of ITS and its domains and not on terms, such as, Computer Aided Learning. Computer Based Training or Computer Based Instructions.

3) This study is not meant for development of an Artificial Neural Network (ANN), it only uses the concepts, such as, Free-forward and Back-propagation, for finding a set of weights that minimizes the global error of the network, which allows the network to learn an internal representation of the previously presented patterns and becomes capable of classifying novel patterns presented as inputs.

4) Knowles (1980) says that the term pedagogy derived from the Greek word 'paidagogos', wherein paid- means "child" and agogos means "leading". As the derivation suggests, pedagogy can refer only to children and teaching or leading them. On the other hand, the term andragogy stems from the Greek word 'aner' with the stem 'andros' meaning "man, not boy" or adult and 'ago' meaning "to lead". These stems make it clear that the two terms refer to 'totally'. In pedagogy, the educational focus is on transmitting the content subject matter in a very teacher-controlled environment. Andragogy, by contrast, is the art and science of helping adults learn. In the Andragogical Model there are five assertions: 1) letting learners know why something is important to learn, 2) showing learners how to direct themselves through information, 3) relating the topic to the learner's experiences; in addition, 4) people will not learn until they are ready and motivated to learn, 5) this requires helping students to overcome inhibitions, abnormal behaviours and biased beliefs about learning" (Conner, 2004). However, in this research context, the term pedagogy is used in conjunction with the term andragogy and refers to all learners who are above the age of 18.

1.11 Organization of this study

Chapter 1 provides a general orientation to the research work: background to the study, problem statement, objectives of the study, research questions, significance of the study, limitations of the study, and definition of operational terms. Chapter 2 comprises a literature review of related studies. Chapter 3 narrates the research methodology, which covers the research sample, research method, research design, method of data collection and analysis techniques. The data analysis and findings of the entire research work are presented in Chapter 4, while the stages of Student Model development and final discussion, summary, recommendations and conclusion make up Chapter 5 and Chapter 6 respectively.

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Appendix 1

SPSS analysis showing Frequencies for practice test scores, real test scores, Final exam scores Frequencies

Statistics

		Final Exam result	Test 1 (L)	Test 2 (M)	Test 3 (H)
N	Valid	104	105	105	105
	Missing	1	0	0	0
Mean		85.0096	8.6857	7.3333	5.9714
Median		88.0000	9.0000	8.0000	6.0000
Std. Deviation		10.18899	1.24278	1.77951	2.37559 -
Skewness		-1.410	-.880	-.707	.224
Std. Error of Skewness		.237	.236	.236	.236
Kurtosis		1.639	.354	.095	-.975
Std. Error of Kurtosis		.469	.467	.467	.467
Minimum		50.00	5.00	3.00	1.00
Maximum		98.00	10.00	10.00	10.00

Frequency table continued

Test 1 (L)

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 5.00	2	1.9	1.9	1.9
6.00	5	4.8	4.8	6.7
7.00	9	8.6	8.6	15.2
8.00	25	23.8	23.8	39.0
9.00	31	29.5	29.5	68.6
10.00	33	31.4	31.4	100.0
Total	105	100.0	100.0	

Test 2 (M)

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 3.00	5	4.8	4.8	4.8
4.00	4	3.8	3.8	8.6
5.00	8	7.6	7.6	16.2
6.00	8	7.6	7.6	23.8
7.00	27	25.7	25.7	49.5
8.00	24	22.9	22.9	72.4
9.00	20	19.0	19.0	91.4
10.00	9	8.6	8.6	100.0
Total	105	100.0	100.0	

Frequency table continued

Test 3 (H)

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 1.00	2	1.9	1.9	1.9
2.00	7	6.7	6.7	8.6
3.00	13	12.4	12.4	21.0
4.00	8	7.6	7.6	28.6
5.00	12	11.4	11.4	40.0
6.00	16	15.2	15.2	55.2
7.00	14	13.3	13.3	68.6
8.00	15	14.3	14.3	82.9
9.00	14	13.3	13.3	96.2
10.00	4	3.8	3.8	100.0
Total	105	100.0	100.0	

Frequency table continued

Real test scores

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1	1.0	1.0	1.0
	2.00	1	1.0	1.0	1.9
	3.00	2	1.9	1.9	3.8
	4.00	6	5.7	5.7	9.5
	5.00	17	16.2	16.2	25.7
	6.00	18	17.1	17.1	42.9
	7.00	24	22.9	22.9	65.7
	8.00	18	17.1	17.1	82.9
	9.00	17	16.2	16.2	99.0
	10.00	1	1.0	1.0	100.0
	Total	105	100.0	100.0	

Appendix 2

Reliability test carried on the practical test and real test scores

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	105	100.0
	Excluded[a]	0	.0
	Total	105	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.707	4

Appendix 3

Test of Normality Practice test scores and Real test scores Explore

[DataSet1] C:\Users\Arman\Desktop\3) RAVI\SPSS\DATA\Ravi - 1.sav

Descriptives

			Statistic	Std. Error
Score	Mean		6.6667	.17366
	95% Confidence Interval for Mean	Lower Bound	6.3223	
		Upper Bound	7.0110	
	5% Trimmed Mean		6.7593	
	Median		7.0000	
	Variance		3.167	
	Std. Deviation		1.77951	
	Minimum		.00	
	Maximum		10.00	
	Range		10.00	
	Interquartile Range		3.00	
	Skewness		-.692	.236
	Kurtosis		.908	.467

Test of Normality Practice test scores and Real test scores continued

Test 1 (L)	Mean		8.6857	.12128
	95% Confidence Interval for Mean	Lower Bound	8.4452	
		Upper Bound	8.9262	
	5% Trimmed Mean		8.7831	
	Median		9.0000	
	Variance		1.545	
	Std. Deviation		1.24278	
	Minimum		5.00	
	Maximum		10.00	
	Range		5.00	
	Interquartile Range		2.00	
	Skewness		-.880	.236
	Kurtosis		.354	.467

Test of Normality Practice test scores and Real test scores continued

Test 2 (M)	Mean		7.3333	.17366
	95% Confidence Interval for Mean	Lower Bound	6.9890	
		Upper Bound	7.6777	
	5% Trimmed Mean		7.4233	
	Median		8.0000	
	Variance		3.167	
	Std. Deviation		1.77951	
	Minimum		3.00	
	Maximum		10.00	
	Range		7.00	
	Interquartile Range		2.00	
	Skewness		-.707	.236
	Kurtosis		.095	.467

Test of Normality Practice test scores and Real test scores continued

Test 3 (H)	Mean		5.9714	.23183
	95% Confidence Interval for Mean	Lower Bound	5.5117	
		Upper Bound	6.4312	
	5% Trimmed Mean		6.0026	
	Median		6.0000	
	Variance		5.643	
	Std. Deviation		2.37559	
	Minimum		1.00	
	Maximum		10.00	
	Range		9.00	
	Interquartile Range		4.00	
	Skewness		-.224	.236
	Kurtosis		-.975	.467

	Kolmogorov-Smirnov[a]			Shapiro-Wi k		
	Statistic	Df	Sig.	Statistic	df	Sig.
Real test	.146	105	.000	.937	105	.000
Test 1 (L)	.209	105	.000	.865	105	.000
Test 2 (M)	.188	105	.000	.922	105	.000
Test 3 (H)	.118	105	.001	.951	105	.001

Test of Normality Real test scores and Final scores

Explore Descriptives

			Statistic	Std. Error
Real test	Mean		6.6667	.17366
	95% Confidence Interval for Mean	Lower Bound	6.3223	
		Upper Bound	7.0110	
	5% Trimmed Mean		6.7593	
	Median		7.0000	
	Variance		3.167	
	Std. Deviation		1.77951	
	Minimum		.00	
	Maximum		10.00	
	Range		10.00	
	Interquartile Range		3.00	
	Skewness		-.692	.467
	Kurtosis		.908	

Test of Normality Real test scores and Final scores continued

Final Exam Mean		85.0619	.99093
95% Confidence Interval for Mean	Lower Bound	83.0968	
	Upper Bound	87.0270	
5% Trimmed Mean		85.9524	
Median		88.0000	
Variance		103.104	

	Statistic	Std. Error
Std. Deviation	10.15403	
Minimum	50.00	
Maximum	98.00	
Range	48.00	
Interquartile Range	11.50	
Skewness	-1.425	.236
Kurtosis	1.687	.467

Test of Normality Real test scores and Final scores continued

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Real test	.146	105	.000	.937	105	.000
Final Exam	.202	105	.000	.851	105	.000

a. Lilliefors Significance Correction

Appendix 4

Test of Linearity

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Final Exam * Real test	105	100.0%	0	.0%	105	100.0%

Report

Final Exam

Real test	Mean	N	Std. Deviation
.00	90.0000	1	.
2.00	87.0000	1	.
3.00	66.0000	2	14.14214
4.00	79.1667	6	10.18659
5.00	80.2647	17	11.71820
6.00	81.7778	18	11.53795
7.00	87.4167	24	6.81378
8.00	88.0000	18	8.54056
9.00	90.2353	17	7.26747
10.00	95.0000	1	.
Total	85.0619	105	10.15403

Test of Linearity continued

ANOVA Table

			Sum of Squares	df
Final Exam * Real test	Between Groups	(Combined)	2390.952	9
		Linearity	1467.379	1
		Deviation from Linearity	923.574	8
	Within Groups		8331.895	95
	Total		10722.848	104

ANOVA Table

			Mean Square
Final Exam * Real test	Between Groups	(Combined)	265.661
		Linearity	1467.379
		Deviation from Linearity	115.447
	Within Groups		87.704
	Total		

ANOVA Table

			F	Sig.
Final Exam * Real test	Between Groups	(Combined)	3.029	.003
		Linearity	16.731	.000
		Deviation from Linearity	1.316	.245
	Within Groups			
	Total			

Measures of Association

	R	R Squared	Eta	Eta Squared
Final Exam * Real test	.370	.137	.472	.223

Appendix 5

Discriminant Function Analysis

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Test 1 (L)	.788	13.613	2	101	.000
Test 2 (M)	.471	56.663	2	101	.000
Test 3 (H)	.569	38.227	2	101	.000
Range of Real Test	.952	2.559	2	101	.082
Range of Final Marks	.753	16.556	2	101	.000

Analysis 1

Box's Test of Equality of Covariance Matrices

Log Determinants

Category	Rank	Log Determinant
Low	5	-8.602
Medium	5	-7.050
High	5	-8.433
Pooled within-groups	5	-7.246

Discriminant Function Analysis continued

Test Results

Box's M		51.285
F	Approx.	1.503
	df1	30
	df2	3599.160
	Sig.	.039

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.958[a]	94.3	94.3	.814
2	.119[a]	5.7	100.0	.326

a. First 2 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.302	118.508	10	.000
2	.893	11.155	4	.025

Discriminant Function Analysis continued Standardized Canonical Discriminant Function Coefficients

	Function	
	1	2
Range of Test 1	.315	.102
Range of Test 2	.728	.028
Range of Test 3	.497	-.561
Range of Real Test	-.251	-.282
Range of Final Marks	.185	.903

Structure Matrix

	Function	
	1	2
Range of Test 2	.757*	-.029
Range of Test 3	.612*	-.438
Range of Test 1	.369*	.174
Range of Final Marks	.363	.763*
Range of Real Test	.155	-.172*

Discriminant Function Analysis continued

Functions at Group Centroids

Category	Function 1	Function 2
Low	-2.526	-.706
Medium	-.634	.302
High	1.583	-.181

Classification Statistics

Classification Function Coefficients

	Category		
	Low	Medium	High
Test 1 (L)	6.887	8.350	9.708
Test 2 (M)	4.433	7.544	11.083
Test 3 (H)	.845	1.522	4.002
Real Test	.744	-.444	-1.103
Final Marks	10.859	14.007	13.939
(Constant)	-23.916	-38.625	-53.548

Classification Results[a]

		Category	Predicted Group Membership: Low	Medium	High	Total
Original	Count	Low	9	3	0	12
		Medium	6	42	4	52
		High	0	8	32	40
	%	Low	75.0	25.0	.0	100.0
		Medium	11.5	80.8	7.7	100.0
		High	.0	20.0	80.0	100.0

a. 79.8% of original grouped cases correctly classified.

Appendix 6

Operational definitions

1 Adaptive Tutoring System (ATS)

Adaptive learning is a computer-based and/or online educational system (Learning environment) that modifies the presentation of material in response to student performance. In the context of this study, Adaptive Tutoring System is one in which students are exposed to an Adaptive learning environment.

2 Adaptive Feedback System

Gheorghiu and Vanlehn (2008) suggested that meaningful, constructive and adaptive feedback is the essential feature of ITSs, and it is such feedback that helps students achieve strong learning gains.

3 Aptitude test

It is one of the most commonly used assessments in measuring candidates' suitability for a role. However, in the context of this study, Aptitude test refers to Multiple Choice Question based tests that are used to assess the students' knowledge in a particular subject domain.

4 Artificial Intelligence (AI)

Artificial intelligence (AI), is an area of computer science that emphasizes the creation of intelligent machines that work and react like humans.

5 Authoring Tools

To create a proper course for eLearning, you need an authoring tool to facilitate this work. The definition of authoring tool is “a program that helps you write using hypertext or multimedia applications and enable you to create a final application merely by linking together objects, such as a paragraph of text, an illustration, or a song. By defining, the objects' relationships to each other and by sequencing them in an appropriate order, authors those who use authoring tools can produce attractive and useful graphics applications (Webopedia, 2003).

6 Authoring System

An authoring system is a program that has pre-programmed elements for the development of interactive multimedia software titles. Authoring systems is a software that allows its user to create multimedia applications for manipulating multimedia objects (Wikipedia, 2007).

8 Behaviorism

It is a theory that psychology is essentially a study of external human behavior rather than internal consciousness and desires.

9 Cognitivism

It is the study in psychology that focuses on mental processes, including how people perceive, think, remember, learn, solve problems, and direct their attention to one stimulus rather than another.

10 Cognitive Science

It is an interdisciplinary science that draws on many fields (as psychology, artificial intelligence, linguistics, and philosophy) in developing theories about human perception, thinking, and learning.

11 Computing Linguistics

It is an interdisciplinary field concerned with the statistical or rule-based modeling of natural language from a computational perspective.

12 Computer Based Tutorials

Computer Based Tutorials (CBT's) are the training modules that help you to impart training in a very interactive and entertaining manner.

13 Conceptual framework

According to Miles and Huberman (1994, p18), "conceptual framework explains graphically or by narration, the main things to be studied – the key factors, concepts and variables – and the presumed relationship among them".

14 Constructivism

It is a learning theory found in psychology, which explains how people might acquire knowledge and learn.

15 Domain Module

Domain model contains the knowledge about design patterns an d the actual teaching material.

16 e Learning

It is learning utilizing electronic technologies to access educational curriculum outside of a traditional classroom. In most cases, it refers to a course, program or degree delivered completely online.

17 Expert Model

An expert model is a computer representation of a domain expert's subject matter 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 what the user does and doesn't know.

18 Formative assessment

Formative assessment is a process used by teachers and students during instruction that provides explicit feedback to adjust ongoing teaching and learning to improve students' achievement of intended instructional outcomes (McManus, 2006).

19 General Student Model

The General Student Model (GSM) framework consists of a database, for the storage of student information and meta-data on the structure of the student information; a web service; to allow learning environments to dynamically retrieve and update student informaiton; a programming interface, for the interaction between the GSM and the individual leanring environment; and a web interface, to allow researchers to specify the form of student data that will be stored (Smith, 2007).

20 Intelligent Tutoring System

Intelligent Tutoring System definitions has its origin dated back to as old as 1984, where Joseph and Sharon states, Intelligent Tutoring System (ITS) is a computer system that aims to provide immediate and customized instruction or feedback to learners. However, in the context of this study, ITS is seen as a system that comprises of consist of four basic components based on a consensus amongst researchers (Nkambou et al., 2010). Added to it, by definition, intelligent tutoring systems (ITSs) are computer based instructional systems that attempt to gather information about a learner's learning status and having this information try to adapt the instruction to fit the learner's needs. Based on the definition, ITSs try to satisfy all needs of an individual learner, especially with personalization and individualized instruction (Moundridou & Virvou, 2003).

21 Interface Model

The interface module supports to intend for the students to interrelate with system. Commonly through a graphical user interface. Sometime, through simulation of the task domain for the students' learning.

22 Neural Network (NN)/ Artificial Neural Network

A neural network is a system of programs and data structures that approximates the operation of the human brain. A neural network usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access to data in its local memory. Typically, a neural network is initially "trained" or fed large amounts of data and rules about data relationships. A program can then tell the network how to behave in response to an external stimulus or can initiate activity on its own.

Source: http://searchnetworking.techtarget.com/definition/neural-network.

23 OCR (Optical Character Recognition)

OCR lets you convert images with text into text documents using automated computer algorithms.

24 Online Learning Environment (OLE)

As technology is growing at tremendous speed, it is always a difficult task to define an Online Learning Environment. Within the last ten years, there seems to be more congruence in the use of the terms defining learning environments where the definitions all use words, which suggest that learning is occurring in a specific web-based area. One such term is an Online Learning Environment (OLE) and it can be assumed that the above terms can all be referenced by this term (Asunka, 2008; Barnard-Brak, Lan, & Paton, 2010; Khan, 2001; Rhode, 2009; Zhang & Kenny, 2010). As such, in the context of this study, the work OLE refers to any environment where learning occurs in a web-based environment.

25 Pedagogy

Knowles (1980) says that the term pedagogy derived from the Greek stem paid- (meaning “child”) and agogos (meaning “leading”). As the derivation suggests, pedagogy can refer only to children and teaching or leading them. In pedagogy, the educational focus is on transmitting, in a very teacher-controlled environment, the content subject matter. Andragogy, by contrast, is the art and science of helping adults learn. In the andragogical model there are five assertions: 1) Letting learners know why something is important to learn, 2) showing learners how to direct themselves through information, 3) relating the topic to the learner’s experiences. In addition, 4) people will not learn until they are ready and motivated to learn. 5) This requires helping overcome inhibitions, behaviors, and beliefs about learning” (Conner, 2004). However, in this research context, the term pedagogy is used in conjunction with the term andragogy and refers to all learners who are above the age of 18.

26 Pedagogical Module

Pedagogical module provides the knowledge infrastructure necessary to tailor the presentation of the teaching material according to the student mode.

27 Psychometric test

Psychometric analysis is the analysis of psychological tests and measurements to ensure that scores are as reliable and valid as possible. Psychometric analysis can be applied to improve or validate almost any instrument that measures human behavior, performance attitudes, abilities, or personality traits (AR Media Network, 2007).

28 Student Model

The student model "evaluates student performance to determine his or her knowledge and skills" (Ong & Ramachandran, 2000, p 10). By maintaining a record of each user's skills and drawbacks, the ITS can provide effective, individualized instruction (Ong & Ramachandran, 2000). The student model keeps its individualized content in its electronic storage, allowing for easy access to each user (Beck, Stern, & Haugsjaa, 2004). The information gathered shows what the system sees as the learner's current skill level (Beck, Stern, & Haugsjaa, 2004). However, in the context of this study we shall use the definition specified by Beck, Stern & Haugsiaa (2004), which states, a student model should contain a record of the student's understanding of the material, as well as more general information about the student such as learning preferences, acquisition and retention (Beck, Stern, & Haugsjaa, 2004).

29 Theoretical framework

Theoretical framework is a conceptual model of how one theorizes or makes logical sense of the relationships among several factors that have been identified as important to the problem (Sekaran, 2000).

30 Tutor Model

It is part of an Intelligent Tutoring System which is triggered when the system finds a mismatch between a student’s behavior or knowledge, and the expert’s presumed behavior or knowledge, which subsequently act to provide feedback or remedial instruction (Chris Daly, 2009).