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Implementation and Evaluation of Intelligence Incorporated Tutoring System

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Abstract*: *This research article elaborates the explication of domain knowledge into a tutorable form and illustrates the prediction of tutoring strategy prior to beginning of the tutoring session. The proposed intelligent tutoring system is christened as SeisTutor. It impersonates human intelligence by adjudging best tutoring strategy for the learner. An empirical analysis has been performed on group of applicants having fundamental knowledge of the domain. Experimental analysis reveals that the learners who have undergone tutoring through 'SeisTutor' embedded with intelligence present an overall 44.5 % learning gain as against that of 24.8 % shown by learners who underwent tutoring through the 'SeisTutor', while it does not impersonate intelligence by choosing content and style for the learner.

Keywords* : *Course Dependency Graph, , Fuzzy Inference System, Intelligent tutoring system Knowledge management, Knowledge Repository.

I. INTRODUCTION

In recent times 'Artificial Intelligence' has emerged as a strong area of research. It has paved its way to success, in the field of education, specially by providing an effective way of teaching and learning. This effective method has been made possible by design and development of in various educational computer artifacts. These developments have given rise to a whole new field of intelligent tutoring. With the amalgamation of disciplines of computer science, cognitive psychology and educational research, the field of intelligent tutoring has gained immense popularity in the present times predominantly due to the development of artifacts Intelligent Tutoring Systems (ITS) [1]. These systems, called cognitive tutors, offer the an appropriate tutoring methodology for the learners according to their learning preference. This program, apart from behaving like a human tutor, adapts the rules and instructions based on the progress and behavior of the learner. ITS is an intelligent computer system that answers the issues that a learner may have by giving appropriate feedback and hints. ITS not only tracks the learner's activity but also predicts the learner's proficiency on subject matter and attempts to understand the learner's psychological mindset. As, the tutoring system cognizes psychological mind by solving the learner's issues and offering the tutoring content to the learner in an easy and effective way, it is termed as an "intelligent" tutoring system. An ITS substantially differs from a typical e-learning system, like a web-based learning system, which enables a learner to explore a specific domain or course contents via internet. Unlike ITS, these systems fail to adapt to the learner's learning needs and offer learner any specific feedback and hints. The reason for ITS's immense popularity in present time is its extremely adaptive nature. The twentieth century saw rise of the intelligent tutoring systems as one of the most prevalent and effective ways of learning and teaching. However, there are still some traditional comparative studies that depreciate this artificial teaching and learning techniques [2]. Resource sharing and intelligence are the key features of intelligent tutoring systems (ITS) that make it different from the other traditional techniques [3] [4]. Moreover, intelligence of ITS is focused on the learner's cognitive ability therefore it may overlook the real environment and original feelings. Learner cognitive ability can only be achieved when there exists an emotional exchange between the learner and the tutoring system.

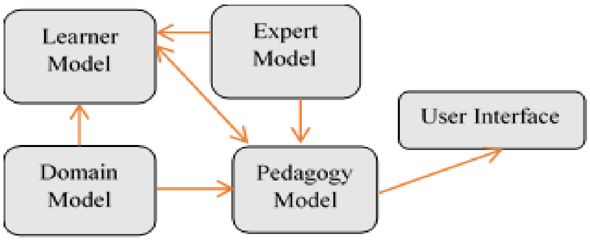

Fig 1 Architecture of Traditional ITS

The effectiveness of personalized tutoring in ITS rely on the coordination of domain model, expert model, pedagogy model and learner model. Following Figure 1 shows the architecture of traditional ITS and brief description of these modules, follows.

A. Domain Model

This model holds the subject matter, that is to instruction through the ITS. As it represents the domain knowledge in a suitable way, knowledge engineering plays a vital role. One way of depiction the same is by way of facts and procedures. A domain model is designed in such a way that system Subject material with ease can access appropriate.

B. Expert Model

This model utilizes expert knowledge skills to represent the domain knowledge in such a manner which improves the problem-solving skills of the learner. This is carried out by sharing chunks or units of knowledge that is taught to the learner.

C. Learner Model

The model highlights the affective and cognitive states of learner with respect to the learning gain. This system keeps a track of the process followed by the learner to solve a particular issue and then traces to the conclusion in order to alter the learning path, as per need.

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D. User Interface Model

This model acting as an interface, amalgamates all the necessary data to communicate with the learner by different media representations, such as click-on event, mouse driven menu, multi-media, and text.

The tutoring system works in a manner that it holds domain knowledge or subject matter capsule which it then offers to its learners. Presented below is the knowledge domain used in the current work.

A petroleum geologist accomplishes petroleum exploration with the purpose to discover geological structures appropriate for hydrocarbon amassing. The geologists and geophysicists use seismic images to describe terrestrial subsurface. This is done by these experts by putting to use their skills and knowledge. The manually interpreted seismic images, nevertheless, produce varying interpretations of the same image according to different seismologists. This happens because there are numerous variables computations involved and there are no absolute set of rules or procedures that all of these seismologists have to abide by. Therefore, each geologist uses his or her own skills, expertise that he or she has established over past years [5].

There is an apparent lack of formal knowledge-base of interpretation rules which causes a dependency on human experts, moreover, it hinders much-needed training/imparting of knowledge to the forthcoming generation. Therefore, this information is available in a tacit form. The transformation from tacit to explicit form is done to facilitate knowledge dissemination, which is much needed for its effective percolation to the younger generation so as to be used in years to come.

Knowledge base creation is itself very expensive, time-consuming and difficult task. A great level of effort is required to develop a domain knowledge base to resolve the problems of learner in a much similar way like a human tutor. The problem becomes worse when knowledge is not well documented anywhere, i.e. it exists in tacit form. Tacit form means the knowledge which is acquired with experience and is available with expert only. Thus gathering such knowledge from domain experts is major challenge. Another issue with tacit knowledge is its representation, meaning the conversion of tacit knowledge into explicit form that is in such a format so that it is widely accessible. This is one of other major bottle-necks involved.

Apart from the problem of creating knowledge base, there lies another challenge in ITS i.e. of sequencing the domain knowledge as per learner preference, understandability and learner imbibing level. This identification of relevant knowledge from the wide pool of domain knowledge and sequencing it according to the need is one of the most important issues key feature of an ITS.

II. PRELIMINARIES

The Successive sections provide a complete coverage of evolution of ITS dating from initial computer assisted instruction systems, to the more advanced systems of present times that incorporates many more intelligence techniques concerned with delivering the learning material as per the learning profile.

In year 1950, the first ITS was modernized in the form of Computer Aided Instruction (CAI) [7] which had pre-decided frames or course material presented in a linear fashion i.e. to achieve the desired goal, the learner has to follow the step by step procedure of sequentially organized frames presented in linear fashion.

To efficiently interact with the learner, an advanced system known as Intelligent Computer Aided Instruction (ICAI) was developed which assisted control over the content [8]. In 1980s, Computer Assisted Instruction (CAI) with AI techniques was introduced by Carbonell's with the purpose to overcome the limitations posed by generative CAI. Further, in 1982, review of progressive development of ITS was presented by Sleeman and Brown as problem-solving monitors, coaches, laboratory instructors, and consultants. [15]

The Andes Intelligent Tutoring System [6] [9] which was developed with the purpose to teach Physics used Bayesian network for effective decision making. The Fuzzy Inference Technique was utilized in InterMediActor,, which used navigation graph data structure to sequence course material. The Fuzzy inference mechanisms and fuzzy sets were used, so that the learner’s knowledge and ability to grasp the subject can be made use of to identify the course content for the learner. To teach SQL through an agent developed using artificial neural network, SQL Tutor is used [10] Furthermore, to teach the concept of computer programming language ‘C++’, a rule based C++ tutor is used. [12] Another dialogue based ITS known as CIRCSIM tutor is developed to teach physiology [13] where dialogues are used to communicate with the learner. In, [14] of years is presented and has been reported that its primary focus has been on the following: customization for different student populations, modular and fine-grained curriculum delivery, and development of rich knowledge repository for instructors to tutor and remediate the learners and customized presentation and assessment. ViSMod is also an ITS for visualizing and inspecting Distributed Bayesian Student Model [16].

III. SYSTEM DESIGN

A. Architecture of Tutoring System

The basic architecture of SeisTutor has been shown in Figure 2. Architecture comprises of different modules: Learner interface, Knowledge organization unit, learner model, pedagogical model, domain knowledge and inference system. Learner model, inference system and pedagogical model comprises of the core of an expert system used for making critical decision during tutoring sessions. The expert system employs various rules in the form of (if-then) rules.

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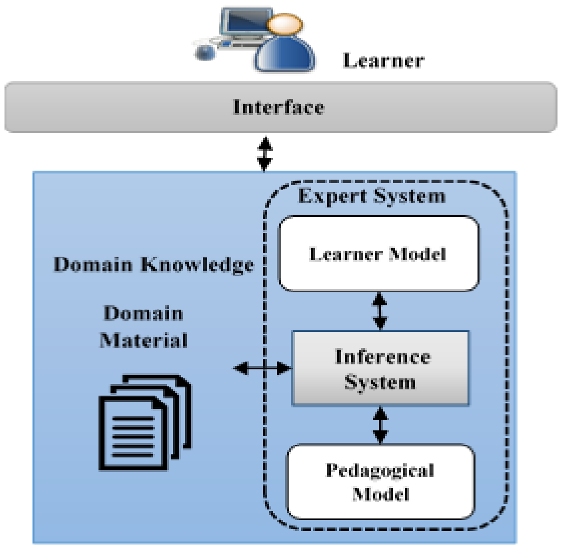

Fig 2 SeisTutor Architecture

Various rules were created based on the specific functionality *(adjudging tutoring strategy, determining the custom-tailored curriculum).* The learner interface offers an adaptive learning environment for the learner to communicate with the SeisTutor. The pedagogical model determines the custom tailored tutoring strategy and curriculum for the learner. The inference system triggers, rules (functionality) based on the circumstances to produce the corresponding conclusion. Learner interface plays a vital role in intelligent tutoring systems, it not only controls the overall functionality of the intelligent tutoring system, but also interacts with the other models and components of SeisTutor whenever it is necessary. Domain knowledge is tutoring related material related to the subject domain. The responsibility of knowledge organization unit is updating and retrieval of the knowledge material contained in domain knowledge of the ITS.

B. Domain Model

Domain model as its name indicates is heart of a SeisTutor, which consist of knowledge base. It systematizes the course concepts, sub concepts and their relationship with the other concepts. This model mainly addresses the "What to Teach" issue.

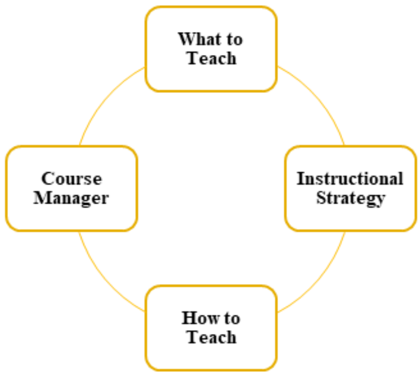

Fig 3 Responsibility of Course Manager

There are two main modules of knowledge base, i.e. course manager and knowledge repository. The responsibility of course manager is to organize and structure the course concepts, sub concepts and relationships. The repository as its name indicates stores the tutoring material and quiz or assessment material. Each learning concept and assessment material is defined by meta-description that helps in locating, maintaining, reusability and representation of knowledge in the knowledge base.

a. Course Manager

It is a schematic representation, of course material. Two data structures are used for its representation, i.e. Concept Tree and Concept Dependency graph. The responsibility of course manager has been shown in figure 3.

i. Concept Tree

Concept tree as its name indicates, it possesses hierarchical tree type structure, in which root node indicates the course name, while leaf node indicates the sub concepts of the course. Figure 4 depicts the course tree structure of subject domain.

ii. Concept Dependency Graph

In the concept dependency graph, nodes indicate the course concepts and sub concepts while arc between them indicates the relationship between them. Every course stored in the knowledge base is represented as a pair of concept tree and a concept dependency graph. Figure 5 depicts the course dependency graph between concepts and sub concepts.

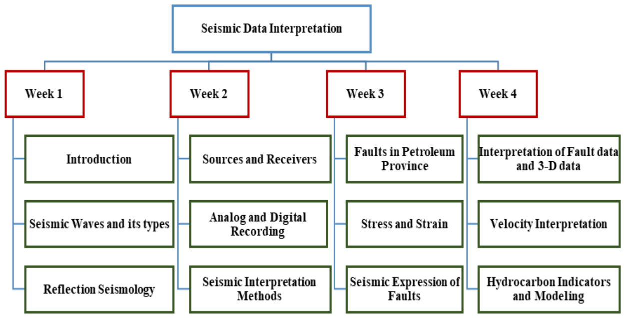

Fig 4 Course-Tree Of Domain-Knowledge 'Seismic Interpretation'

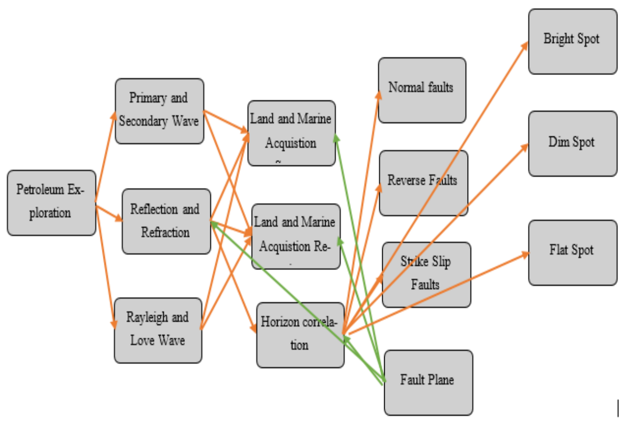

Fig 5 Course Dependency Graph between concepts and sub-concepts

b. *Knowledge Repository*

Knowledge repository is a collection of tutoring and testing materials. For fast accessing of tutoring material from the knowledge pool, the learning units are provide the meta description of the material that helps the concept selection for a learner- specific gathering of learning material.

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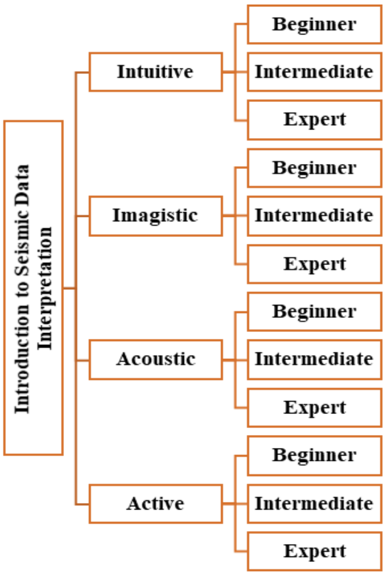

Fig 6 Domain Pedagogical structure in SeisTutor Intelligent Tutoring System (Learning Style and Learner Profile).

The general problem in the present teaching system is overcome by ontologies [4]. Meanwhile web offers interactive media rich learning materials using images, texts, examples, audio, etc. which induce the active interaction between computer system and learner [5]. Active interaction not only enhance the persuasive communication but also improves the Learning gain and problem solving skills. Therefore, ontology based delineation structure for domain knowledge is constructed. This structure helps to enhance the sharing of learning materials and the fusion of learning material with this structure helps SeisTutor to satisfy the different multimedia preferences of learner. A three level knowledge base frame is illustrated in figure 7.

Learning Strategy Level: Current System comprises 12 Tutoring strategy based on different multimedia style using different media (Image, Text, Video, etc) based on level of difficulty (Learner Profile) and Learning Preferences (Learner's Learning style) as shown in figure 6.

Course Level: the learning course content and the hierarchical structure of course content form a course plan grid.

Knowledge Concept Level:

The domain knowledge concepts and their hierarchical structure form the course grid structure. It also retains the concept dependency among concepts (prerequisite, part-of).

A domain knowledge concept gears with abundance multimedia incorporated learning materials. SeisTutor gathers part of learning material from knowledge base based on the learner learning preference and knowledge level. Further, systematize these material based on distinct curriculum determined by SeisTutor.

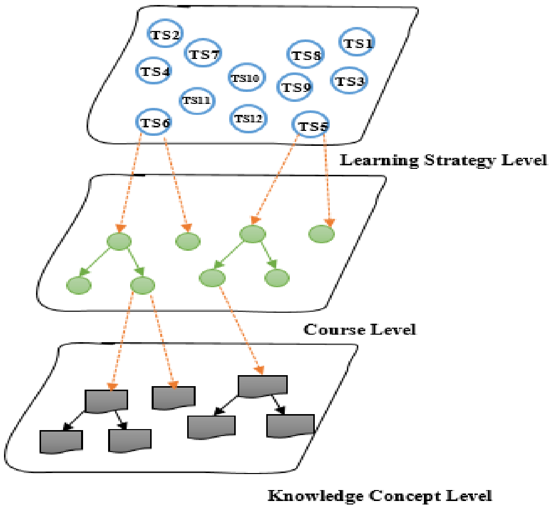

Fig 7 Three level knowledge base frame

Formally, the domain knowledge is defined as follows:

Definition:

A formal representation of domain knowledge base illustrated as follows:

$$DKB_{SDI} = < LS, KC, KCR, CU, CUR, KC_{Update}, CU_{Update} > \quad (1)$$

$LS = \{TS_1, TS_2, TS_3 \ldots \ldots \ldots, TS_{12}\}$ It is sets of learning or tutoring strategy, among which one is chosen (best suits the learner preferences) by SeisTutor to begin the tutoring session.

$CU = \{CU_1, CU_2, CU_3, \ldots \ldots \ldots\}$ It is set of course units, covered during tutoring session.

$KC = \{KC_1, KC_2, KC_3, \ldots \ldots\}$ It is set of knowledge concepts used to explains the topic completely.

$KCR = \{KCR_1, KCR_2, KCR_3, \ldots \ldots\}$ Knowledge concept relation defines relationship between concepts (prerequisite, part-of).

$CUR = \{CUR_1, CUR_2, CUR_3, \ldots \ldots\}$ Concept unit relationship defines the relationship between courses. Here relationships are like how one topic is related (part-of, prerequisite) to other topics.

KC_{Update}: it is a knowledge concept update function used by the domain expert to accomplish the necessary amendments in the knowledge concept course grid.

CU_{Update} : it is a Concept unit update function used by the domain expert to accomplish the necessary amendments in the concept unit.

C. Expert System

a. Learner Model

This model keeps track of learner activity and takes the necessary actions to fulfil the learner needs. This model facilitates four major operations: a) gather learner demographic information, b) gather learner characteristics information's, c)

learner specific designed curriculum and d) custom-tailored tutoring material.

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i. Demographic Information

Demographic information comprises of a general information related to the learner such as name, age, gender, highest qualification, and email-id. SeisTutor uses this information for creating Learner Account.

ii. Learner Characteristic Information

Learner characteristics contains the implicit information gathered by SeisTutor, i.e. learner learning style and learner learning preferences. Based on this information Learner Profile and learning style is distinguished. These characteristics can be adjudged by two test, "knowledge test" and "Learning style test". Both the tests consist of 20 and 18 questions each that are presented to the learner. Knowledge test determines the level of knowledge the learner has before the tutoring session is commenced. Table 1 describes the preferred media corresponding to I^2A^2 Learning style. I^2A^2 learning style model is acronym used of its four learning style *"Imagistic", "Intuitive", "Acoustic" and "Active".*

Table 1 Preferred Media Corresponding To I^2A^2 Learning Style.

Learning Style	Key Terms	Preferred Multimedia
Imagistic (I)	Learning through observing	Videos, flowcharts, diagram, symbols and charts.
Intuitive (I)	Learning through interpretation of written word	Action charts, written paragraph, written notes.
Acoustic (A)	Learning through hearing	Listening, reading notes, group learning and underline information
Active (A)	Learning through action	Hand-on Exercise, extra exercise, experiment based works and color coding technique.

iii. Learner specific designed curriculum

The learner specific designed curriculum provides the custom-tailored curriculum specifically designed for the learner. The focus of this module is to provide a learner with exclusive course content sequenced as per learner level and preference. The idea is to develop a system closest in terms of expressing empathy to the learner, with a larger aim of making learning happen. The questionnaire in knowledge test was designed in such a manner that each question possesses one-to-one and many-to-one relation to the course topics. Learner model records learner response during the test. The response of the learner may show that he/she has got a few questions incorrect, then his/her custom-tailored learning path will majorly comprise of those concepts and concept subgroups rather than of those concepts and concept subgroups whose responses were correctly quoted. The custom tailored tutoring material comprises of tutoring material, organized as per the formulated curriculum for the learner. Thus, when the curriculum is determined, learner module retrieves the tutoring material by accessing the curriculum from one of the knowledge capsules as per the learner characteristics.

Algorithm:

Input: Outcomes of Pre-Knowledge level Test

Output: Exclusive curriculum design for the learner

Begin

1. Retrieve the answers opted by the leaner for the given set of questions Q in a variable $RT = \{R_1, R_2, R_3, \dots\dots, R_n\}$. Where RT is a set which enclose, learner's responses, Q is the set of asked questions, and $R_1, R_2, R_3, \dots\dots, R_n$ are respective learner responses.
2. Matching operation is performed between received results and the master copy of answers, which is stored the database. $MA = \{A_1, A_2, A_3, \dots\dots, A_n\}$. Where MA is a set which encloses correct responses and $A_1, A_2, A_3, \dots\dots, A_n\}$ are the respective correct answers.
3. Separate sets of correct responses $Q_{Correct}$ and incorrect responses Q_{wrong} were created.
   do
   - 3.1. $\{$
   - 3.2. $if\ (R_i == A_i)$
   - 3.3. $\{$
   - 3.4. $Q_{correct} = Q_i\ ;$
   - 3.5. $\}$
   - 3.6. $else$
   - 3.7. $\{$
   - 3.8. $Q_{wrong} = Q_i\ ;$
   - 3.9. $\}$
   - 3.10. $i++;$
   - 3.11. $\}$ $i \leq n$ $//\ where\ n\ is\ the\ number\ of\ questions\ asked\ in\ Pre-Knowledge\ Pretest$
   - 3.12. while ( );
4. Step 2 and 3 will repeat for all the response until while condition met.
5. Q_{wrong} Sets are taken into the consideration and perform a mapping operation between the topics covered and Q_{wrong} sets.
   $for\ (k = 1; k \leq n; k++)$
   - 5.1. $\{$
   - 5.2. $for\ (l = 1; l \leq n; l++)$
   - 5.3. $\{$
   - 5.4. $if\ \left(Q_{wrong_k} == W_k == T_l\right)$
6. $W = \{W_1, W_2, W_3, \dots\dots, W_n\}$ *// where* W *is a set which enclose the labels (that directly links to the topics) and are the respective labels associated with the questions.*
   - 6.1. $\{$
   - 6.2. $Topic = T_l\ ;$
   - 6.3. $\}$
   - 6.4. $else$
   - 6.5.

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{

6.6. continue ;

6.7. }

6.8. }

6.9. }

6.10. Topic

7. Set consists of the course collection which is exclusively designed for the learner by the SeisTutor.End

b. Pedagogical Model

The pedagogical model is the heart of intelligent tutoring system, because it makes the vital pedagogical decisions during the tutoring sessions. It executes the tutoring strategy.

i. Tutoring Strategy Selection

The teaching of tutoring material depends on several instructional strategies which can be interactively regulated by human instructor through face to face interaction. In similar manner, the intelligent tutoring system decides the suitable tutoring strategy for tutoring a concept/ sub concept contingent on some attributes (see Figure 7).

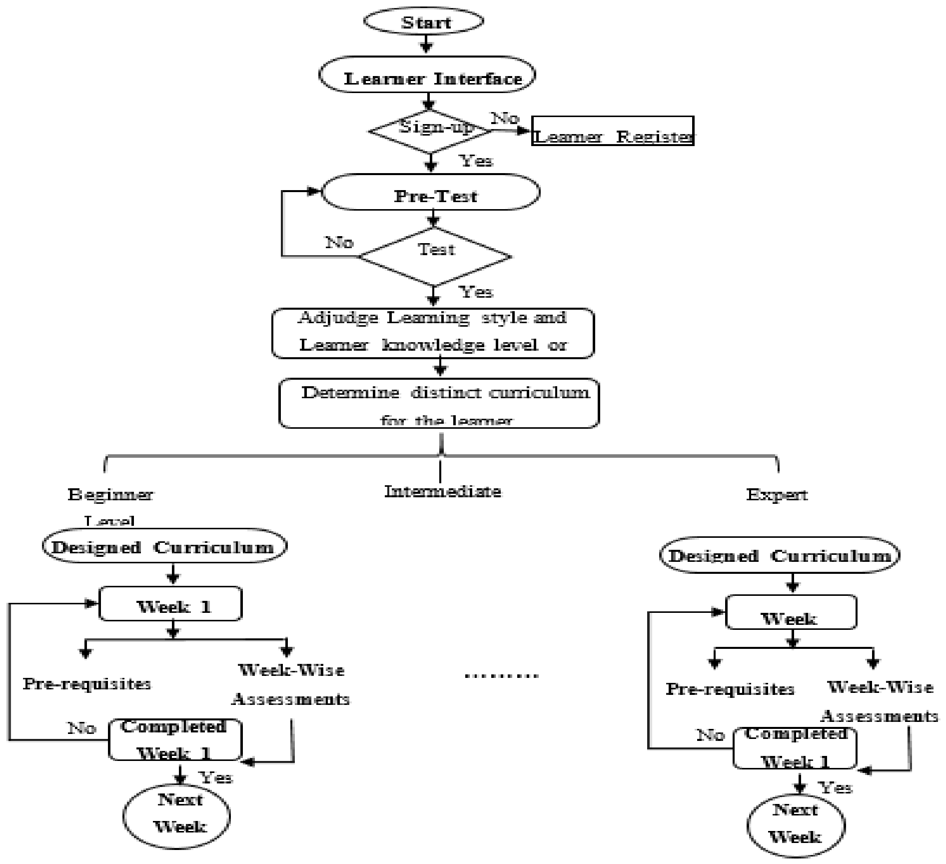

Figure 7 Course Overview

i. Fuzzy Inference System

Mamdani fuzzy inference system generally acts as a foundation for building fuzzy inference methods, because previously it has been successfully used in several intelligent tutoring systems (ITS). Rules that have highest activation value help to converge towards the result of fuzzy classification system. Fuzzy inferencing comprises of various conditional statements formulated in form of If-then rules.

$$Rule\ i: IF\ C_1\ AND\ C_2\ THEN\ C_3 \quad (2)$$

For better understanding, Let us consider the fuzzy state computation for determining tutoring strategy. For learner L, initially when learner logs in into the system he or she has not covered any tutoring concepts.

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Based on the performance and interaction with the tutoring system his or her knowledge level may get altered. After completion of pretest SeisTutor has Learning style test score (LSS_T) and Knowledge level test score (KLS_T). There are 18 questions in learning style test, where each question consists of 4 choices and each choice belongs to some learning style. Thus, the value for each learning style lies from [0-18]. Therefore, at the end of the test, the learning style having highest value gets selected for further processing and its value is stored in (LSS_T). The knowledge level test comprises of 20 questions. Here the case is different, i.e. value of (KLS_T) equals to the number of correct responses given by the learner during test. As soon as the pretest is over SeisTutor has both (LSS_T) and (KLS_T) values. The linguistic variable used in knowledge level test is *{"Beginner", "Intermediate", and "Expert"}*.

$$x = \frac{KLS_T}{2} \quad KLS_T = [0-20] \qquad (3)$$

The membership function of fuzzy state for knowledge level is as follows:

$$\mu_{Beginner} = x \text{ where } 0 \leq x < 3.5 \qquad (4)$$

$$\mu_{Intermediate} = x \quad \text{where } 3.5 \leq x < 7.0 \qquad (5)$$

$$\mu_{Expert} = x \quad \text{where } 7.0 \leq x \leq 10 \qquad (6)$$

$$TutoringStrategy_i = \begin{Bmatrix} TS1, TS2, TS3, TS4, TS5, TS6, TS7, \\ TS8, TS9, TS10, TS11, TS12 \end{Bmatrix}$$

Let us consider an example,

Suppose learner highest pretest learning style test score is for Imagistic 11

i.e. $LSS_T = \mu_{Imagistic}$ (7)

As aforementioned there are total 12 learning style, in which a tutoring content is designed.

$$Rule\ i: IF\ Knowledge_{level} is\ \mu_{Beginner}(2.5)\ AND\ IF\ Learning_{style}\ is\ \mu_{Imagistic}\ (11)\ THEN\ Tutoring_{strategy}\ is\ ImagisticBeginner$$

ii. Concept Selection Agent

As per the response from the Fuzzy inference system and learner specific designed curriculum the learning concepts from the domain knowledge is reterived. After gathering, make use of tree data structure for populating the tutoring concepts on learner dashboard.

IV. EXPERIMENTAL ANALYSIS

The SeisTutor has been tested on select population of students pursuing anonymous Indian university. Total 60 learners were participants of this study. Based on their interest these learners were given as choice to either enroll as part of groups, study 1 or study 2.

Study 1: In study, the effectiveness of SeisTutor is tested. Here learner has chosen to learn the tutoring content via SeisTutor interface, while it impersonates the human intelligence.

Study 2: In Study 2 learners learn the tutoring content by SeisTutor interface, while it is not impersonating the human intelligence.

Total 28 learners opted to learn under Study 1 and remaining opted to learn under Study 2. All applicants firstly create a SeisTutor learner account and receive unique learner Identity. After creating account applicants undergo Pretest. Pretest comprises of two tests i.e. learning style test and knowledge level test. Table 2 indicates the applicant's demographic information.

Table 2 Learner's Demographic information

Demographic Characteristics			
Characteristic		**N= 60**	
		Frequency	**Percentage**
Gender	Male	35	58 %
	Female	25	42 %
Age	18-20	7	12 %
	20-22	11	18 %
	22-24	11	18 %
	24-28	3	5 %
	28-32	7	12 %
	32-34	13	22 %
	>34	8	13 %
Education	Diploma	0	0 %
	High/ Secondary School	18	30 %
	Graduation	10	17 %
	Post-Graduation	21	35 %
	Ph.D	11	18 %
Occupation	Student	18	30 %
	Teacher	11	18 %
	Both (Teacher & Student)	19	32 %
	Others	12	20 %

To determine, their willingness to participate in evaluation process, a consent form illustrating, important details of the process, was circulated amongst volunteers. It is mandatory for each participant to give their consent for participation in the evaluation process. As evident from Table 2, a higher percentage of learner population (58 %) was male as against female participants. Majority of the participants were holding post-graduation (35 %) as their highest qualification. SeisTutor is solely developed for "Seismic Data Interpretation" subject domain. Thus, it is aimed, for use by learners, belonging to petroleum engineering and exploration domain. The complete mix of participants included undergraduate learners (B. Tech Petroleum engineering), Teachers (Petroleum Engineering department and others, mainly practitioners (from public sector undertaking company belonging to exploration industry).

After registration SeisTutor offers pretest, and as a result, learner's learning style and learning level were gauged. Based on learning style and profile, the pedagogy style is determined.

Study 1: for applicants of study 1, after giving test their Learner knowledge imbibing level and preferred media are determined. The I^2A^2 learning style model is used for determining the learning style. As elaborated in section 4 tutoring strategy computation using the Fuzzy computation technique is performed.

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Thus, SeisTutor predicts the tutoring strategy and custom-tailored curriculum for the learner. Based on tutoring strategy and curriculum the appropriate media are chosen by pedagogical and learner model and presents the tutoring content is presented via learner interface. Then every learner proceeds with his or her tutoring under determined tutoring strategies.

Study 2: Here every learner receives same content, is offered same curriculum and are tutored by SeisTutor through learner interface.

Table 3. Learning Gain Results

System	Total Participants	Pre-Tutoring Test Score	Post-Tutoring Test Score	Mean Learning Gain
Study 1	28	1.72	3.94	44.4 %
Study 2	32	2.41	3.65	24.8 %

As elaborated in aforementioned Sections 3 and 4 that after completion of a tutoring concept, a post lecture assessment is performed. In which SeisTutor presents 10 questions from the taught material.

These assessments have been done for both the studies. The course curriculum is designed for 4 weeks. Thus, at the end of each week SeisTutor determines both Pre-tutoring score are well as post-tutoring score of every week. For evaluating the learning gains of the learner, the post tutoring and pre-tutoring score are normalized in range [0-10] and the difference in computed

$$LG_l = (PostScore_L - PreScore_L) \quad (7)$$

Using above formula learning gain for each learner is computed. Table 3 illustrate the comparative analysis of learning gain of the studies.

An average learning gain of 60 learners is shown in table 3. The average learning gain is higher for study 1 i.e. 44.4 %. This is may be due to the motivation factor of learners in completing and getting tutoring material as per their preferences and need. The average learning gain for study 2 is around 24.8 %. A lower learning gain attributed to possible distractions and not being able to get tutored as per preferences and level. Thus from the computed results of SeisTutor one can deduce that intelligent SeisTutor helps learners to enhance their learning in the subject domain *"Introduction to Seismic Data Interpretation"*.

Furthermore, a Paired Sample T Test is performed on both Intelligent SeisTutor (Pretest and Posttest scores) and non-Intelligent SeisTutor (Pretest and Posttest scores). This section considers two case studies:

Case 1: A Paired-Sampled-T-Test performed on Study 1.

Hypothesis-Case-1.0: Let the participants involved in Study 1 having similar pretest and posttest mean score (negligible performance improvement).

Hypothesis-Case-1.1: Let the participants involved in Study 1 not having different pre-test and post-test mean scores (effective performance improvement).

Case 2: A Paired-Sampled-T-Test performed on Study 2.

Hypothesis-Case-2.0: Let the participants involved in study 2 having similar pre-test and post-test mean scores (negligible performance improvement).

Hypothesis-Case-2.1: Let the participants involved in study 2 not having similar pre-test and post-test mean scores (effective performance improvement).

The calculate T value (T_{Stats},) for study 1 is 11.410, $P < 0.01$ (see Table 32). On an average posttest scores were 2.21786 point higher than pretest scores. Here the calculated T_{Stats}, is greater that $T_{critical}$, thus hypothesis 1.0 is rejected. From Table 4 and 6 one can deduce with confident that there is significant difference between Pre-test and Post-test scores.

The calculated T value (T_{Stats},) for study 2 is 5.312, $P < 0.01$ (see Table 7). On an average post-test scores were 1.24719 point higher than pre-test scores. Here the calculated T_{Stats}, is greater than $T_{critical}$, thus hypothesis 2.0 is rejected. From Table 5 and 7 one can deduce with confident that there is significant difference between Pretest and Posttest score.

Both the groups reject the null hypothesis, which means both the groups provide effective training. But aim of this research is to identify, which group is having high impact on enhancing the overall learning gain. To conclude the aim T_{Stats} of both the groups are compared. $T_{Stats}$of study 1 is higher than

T_{Stats} of study 2. Thus, study 1 is having significant difference in the post tutoring and pretest scores and provide more effective training than study 2.

Table 4 Statistical results of Paired Sample T-Test of Study 1

Comparison Item	Learning Mode			
	Mean	N	Std. Deviation	Std. error Mean
Posttest of Study 1 Applicants	3.9375	28	.39455	.07456
Pretest of Study 1 Applicants	1.7196	28	.99740	.18849

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Table 5 Statistical results of Paired Sample T-Test of Study 2

Comparison Item	Learning Mode			
	Mean	**N**	**Std. Deviation**	**Std. error Mean**
Posttest of Study 2 Applicants	3.6525	32	.58915	.10415
Pretest of Study 2 Applicants	2.4053	32	1.39565	.24672

Table 6 Paired-Sampled-T-Test results of Study 1

	Mean Difference	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		T Stats	df	T Critics
				Lower	**Upper**			
Pair 1: Posttest of Study 1 – Pretest of Study 1	2.21786	1.02856	.19438	1.81902	2.61669	11.410	27	2.0518

Table 72 Paired-Sampled-T-Test results of Study 2

	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		T Stats (Calc)	df	T Critics
				Lower	**Upper**			
Pair 1: Posttest of Study 2 – Pretest of Study 2	1.24719	1.32804	.23477	.76838	1.72600	5.312	31	2.03951

The conclusion of this analysis is that, the Study 1 surpasses the Study 2 as it provides custom-tailored designed curriculum, identify learner emotions during learning and compute learner overall degree of understanding, that fulfil the learner requirements.

V. CONCLUSION

This research article deliberates the generic SeisTutor architecture, presents detailed discussions on schematic view of learning material in twelve tutoring strategies and also the intelligence of prediction of tutoring strategy. The aim of this article is to empirically analyze and compare performance of two study groups one on SeisTutor exercising its cognitive intelligence similar to a human, while other not utilizing the same. A group of learners which is being tutored via intelligence incorporated SeisTutor attain a 44.4 % learning gain. . A Paired-wise-T-Test is also measured on the similar data sets. The outcome of results indicates that calculated T value (T_Stats,) for study 1 is 11.410, P<0.01. On an average posttest scores were 2.21786 point higher than pretest scores. Here the calculated T_Stats, is greater that T_critical ,thus hypothesis 1.0 is rejected. Therefore, one can deduce with confidence that the study 1 provides effective learning against study 2. The conclusion of this analysis is that, the proposed intelligence approach of SeisTutor surpasses the

without SeisTutor approach as offers learners with tutoring strategy, best suitable to their needs and there by evades the cognitive overload during learning session.

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It is optional. The preferred spelling of the word "acknowledgment" in American English is without an "e" after the "g." Use the singular heading even if you have many acknowledgments. Avoid expressions such as "One of us (S.B.A.) would like to thank ... ." Instead, write "F. A. Author thanks " Sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page.

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