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Implementation and Evaluation of Personalized Intelligent Tutoring System

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Abstract*: This research article illustrates a generic architecture for intelligent tutoring system christened as SeisTutor. SeisTutor adapts itself according to the learner learning preferences by determining the learning style and pre knowledge level. The aim of SeisTutor is to mimic similar the human intelligence by implicitly adjudge the tutoring strategy prior to tutoring session and custom-tailored the tutoring concepts to enhance the learning gain. SeisTutor was implemented using I^2A^2 index of learning style model. An Empirical analysis has been performed for graduation pursing students. The experimental analysis reveals that learning style model were accurately predicted with an accuracy of 61-100 %. The applicants found SeisTutor is helpful with an average of 13 % learning gain, attains 24 % engagement at the beginning of the tutoring session.

Index Terms*: Learning style, Pedagogy flipping, Intelligent tutoring system, e-learning system, domain knowledge, knowledge management.

I. INTRODUCTION

Intelligent Tutoring System (ITS) termed as cognitive tutor, that offer the learning material in a such a manner that best suits the learning preferences of the learner. It is a computer program that not only behaves like a human tutor but also follows some rules and instructions based upon the learner progress and behavior. It cognizes the psychological mind of the learner makes a tutoring system an intelligent tutoring system because it resolves the learner issues and offers the tutoring content in such a manner that learner can grasp easily and effectively [1], [2].

An ITS is distinctly different from a typical e-learning system, which is a web-based learning system, that facilitates a learner to explore a specific domain or course contents via the internet, like ITS these systems don't adapt to the learner learning needs and also don't offer learner-specific feedbacks and hints. ITS being adaptive in nature, has gained immerse popularity in current times. In the last decade Intelligent tutoring system not only used in labs rather it gets explored in workplaces and classrooms and also shows the effective results [3], [4] . Intelligent tutoring system becomes more widely accepted and also prove an effective learning gain, but building Intelligent tutoring system is difficult, expensive and time consuming.

Information and Communication Technology course (ICT) in education aims to develop creative thinking, operational skill and inclusive ability on computer application. However, due to the high strength of learner in class it is very difficult for a human tutor to give dedicated time, meets each individual learner needs and provide necessary guidance [5], [6]. From the literature this has been proven that learner under private tutor could perform better as compare to the traditional didactic methods. The ratio of learner-to-human tutor is large and one-on-one sensitive tutoring has not been possible. This is one of the reasons for developing Intelligent Tutoring System (Machine Tutor) which reduces the large learner-to-human tutor ratio and establish one-to-one interaction, enhances the degree of understandability, provide refined tutoring and also tries to reduce the anxiety of learner. To accomplish aforementioned cognitive features learner model is considered as a core component of ITS [7].

Despite of their immense popularity and remarkable success, it is noted that Intelligent Tutoring System are not the panacea for all learning related problems. Most ITS trying to fulfill the learner's cognitive needs, motivation, engagements and enhance the learning gain. Lack of empathy is the serious limitations of the ITS because motivation, enthusiasm, interest and engagement are precursors of learning and deep thinking [8], [9], [10] .At beginning learner might start the tutoring session with some level of enthusiasm and interest, but boredom certainly steals the learning progress [10],[11],[12],[13],[14],[15].

This article encompasses the designed system architecture that illustrates the functionality of proposed ITS christened as SeisTutor. A SeisTutor utilizes the expert system which makes necessary decisions during the entire tutoring sessions. Expert knowledge is designed using media tools and get triggered via hybrid fuzzy rules. SeisTutor tracks both learners psychological and non-psychological parameters, and based on that it triggered the fuzzy rules that makes the decision of changing pedagogy (*"is there is a need to change the pedagogy or not?"*) or not during tutoring sessions. This article also computed the overall learning gain by performing empirical analysis of computing learner performance, information, satisfaction scale, psychological, non-psychological parameter and engagement scale.

II. SYSTEM DESIGN

A. Architecture of tutoring system:

The basic architecture of SeisTutor has been shown in Fig. 1.

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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 comprise 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.

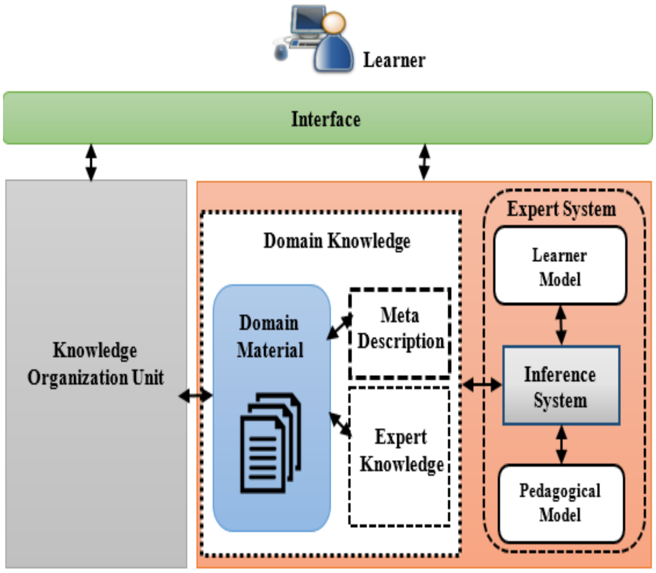

Figure 1 SeisTutor Architecture

Various rules were created based on the specific functionality (adjudging tutoring strategy, determining the custom-tailored curriculum, pedagogy flipping between tutoring session based on psychological and non-psychological parameters, the degree of understandability). The learner interface offers an adaptive learning environment for the learner to communicate with the ITS. 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 it interact with the other models and components of ITS whenever it is necessary. Domain knowledge comprises tutoring related material related to the subject domain. Knowledge organization unit is responsible for updating and retrieving of the knowledge material contained in domain knowledge of the ITS.

III. DOMAIN KNOWLEDGE

Domain knowledge entails information related to subject domain and teaching materials related to the topics to be covered during the tutoring session. It contains three types of information

i) knowledge concepts
ii) meta- description
iii) teaching topics.

Knowledge concept is the fundamental part of knowledge of a domain. Knowledge concepts comprises of numerous attributes such as, name of the concepts, difficulty levels, mode of presentation, detail or explanation level. Every knowledge, concepts are systematized into concept group. Concept group comprises topics that are closely related to the concepts. Therefore, the domain knowledge is divided into sub-domains. As aforementioned, the domain knowledge of the current scope of work is "Seismic Interpretation". Table I illustrates the distinct relation between the concept, concept groups and concept subgroups.

Table I Relation between concept with its group and subgroups.

Concept Group	Concept subgroups	Concept
Seismic Interpretation	Types of Seismic waves	Primary Wave, Secondary Wave, Rayleigh Wave, Love Wave
	Seismic Source and Receivers	Explosion, Vibroseis, Airgun, Geophone, Hydrophone.
	Seismic Interpretation methods	Contouring, Well-Calibration, Velocity Estimation, Depth Maps and Seismogeological Sections.
	Faults is petroleum province	Foot wall, Hanging wall, Normal Fault, Reverse fault, Strike-slip fault
	Hydrocarbons and indicators and modeling	Direct Hydrocarbon Indicators, Bright Spot, Flat Spot, Dim Spot.

Let us consider the example mentioned in table I. "*Seismic Interpretation*" signified as concept groups. In order to elaborate, the actual essence of concept group there may be a possibility that it may characterize into various concept subgroups. Seismic interpretation contains sub-groups '*Types of Seismic waves*', '*Seismic Source and Receivers*', '*Seismic Interpretation methods*', '*Faults is petroleum province*' and '*Hydrocarbons and indicators and modeling*'. As illustrated in table I every subgroup encompasses of number of concepts. Moreover, each concept possesses 'prerequisite relationship' with other concepts. For Example, '*Vibroseis*' possess prerequisite relationship with 'geophone', 'secondary waves', 'primary waves' and 'rayleigh wave' and 'love wave'.

These interrelationships can be viewed as a knowledge graph, so that numerous concept networks are designed expressed as the pedagogical ontological structure of the domain.

The tutoring material consists of various topics, starting from introduction to advanced. Fig. 2 illustrates the ontological relationship between the course-grid of domain knowledge 'Seismic Data Interpretation'.

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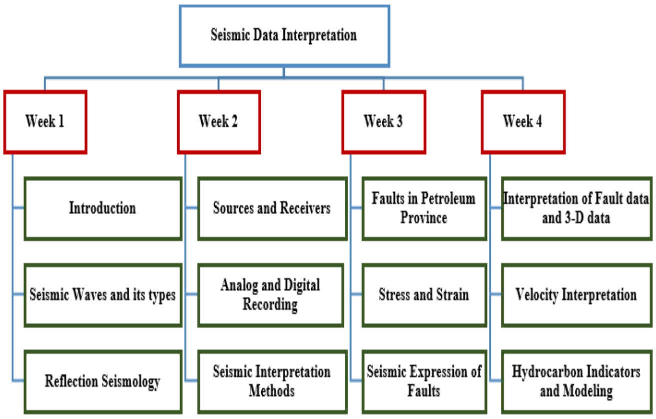

Figure 2 Course-Grid of Domain-Knowledge 'Seismic Interpretation'

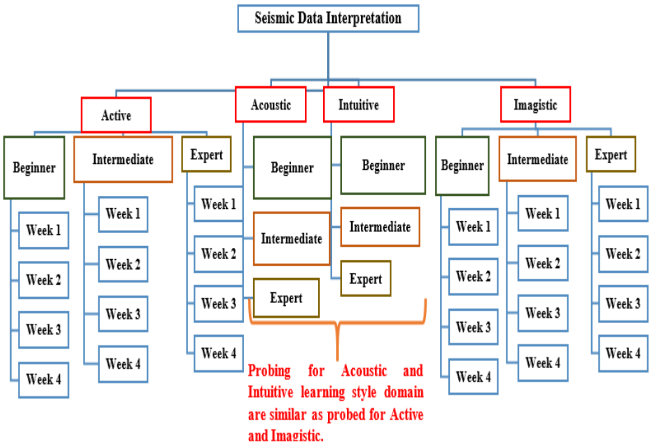

Figure 3 Domain Pedagogical structure in SeisTutor Intelligent Tutoring System (Learning Style and Learner Profile)

Domain knowledge contains a meta-description of the topics included in the course-grid. Current system comprises total 12 tutoring strategy. It means that same course-grid is formalized and arranged in total 12 style using different media on the basis of level of difficulty (Learner Profile) and Learning Preferences (Learner's Learning style) as shown in Fig. 3. From schematic literature review a distinct demonstration of domain pedagogical structure (meta-description and concept network) from its selected tutoring material, not only facilitates better pedagogical decisions, but also the knowledge-updating feature in domain knowledge [16].

IV. Expert System

A. Learner Model

The learning model directly deals with the learner. It means that, the focus of this model is totally dedicated to fulfill its learner needs. Because this model not only records the learner, hidden information, which plays a vital role in learner adaptation operation. This model consists of four types information, i.e. a) Demographic information, b) Performance (non-psychological and Psychological information) parameters, c) Learner characteristics d) learner specific designed curriculum and e) custom-tailored tutoring material. Demographic information includes necessary information used for the creation and management of the learner's account such as learner name, educational qualification, age, email-id, profession and experience. This information is used for the creation a unique learner id, which further used for the identification of the learner. Performance parameter includes information captured during learner interaction with the system. It includes information like, visited the course unit, course unit completion report, correct and incorrect answers in a week-wise assessment, the number of assistants required (Hint taken), total time spend, psychological behavior of the learner during tutoring session.

Learner characteristics define the learner's learning levels (ability to grasp), his or her learning preferences. There are various learner characteristics, like its grasping level, learning media preferences, computer experience. Based on the data acquired, the learner characteristics are adjudge. Learner characteristics can be distinguished as Learner Profile ("Beginner", "Intermediate", "Expert") and learning style ("Active", "Acoustic", "Intuitive", "Imagistic"). These characteristics can be adjudged by two tests, "knowledge test" and "Learning style test". Both the tests consist of 18 questionnaires presented in front of the learner just after the completion of the registration process. The knowledge test determines the level of knowledge the learner has before undergoing the tutoring session. On the basis of Level of difficulty the questions are designed for the knowledge test. Learning style tests determines the mode of learning preference. Table II describes the preferred media corresponding to I2A2 Learning style. I2A2 learning style model is an acronym used of its four learning styles "Imagistic", "Intuitive", "Acoustic" and "Active". In this model the amalgamation of two models is utilized, "Stereotypes" and "Overlay". The Stereotype is used for adjudging the initial profile of the learner, i.e. for the identification of the learner profile and overlay is used for identification of knowledge level. Furthermore, it is used for identification of exclusive curriculum for the learner.

Table II Preferred media corresponding to I2A2 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 the 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.

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The learner specific designed curriculum provides the custom-tailored curriculum that was 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 answers of the learner show that he/she has got a few questions incorrectly, then his/her custom-tailored learning path will mostly comprise of those concepts and concept subgroup and in entail details, instead of those concepts and concept subgroup whose answers are correctly quoted [17].

The custom-tailored tutoring material comprises of tutoring material, organized as per the adjudge curriculum for the learner. Domain Knowledge module comprises of total 12 tutoring strategy or 12 knowledge capsules i.e. material can be organized in twelve styles (combination of learning profile and learning style). Thus, when the curriculum is determined, learner module retrieves the tutoring material by referring the curriculum from one of the knowledge capsules as stated in learner characteristics.

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 adjudges the tutoring strategy, determine the exclusive curriculum, track the Affection (Psychological) state of the learner, track performance parameter, it takes the pedagogy flipping decision and also compute the learner post tutoring performance measure (Degree of understandability, Degree of engagement and Learning gain). It offers the knowledge structure for tailoring the demonstration of tutoring material as per the information gathered in learner model. The pedagogical model consist of four features: a) Tutoring strategy selection b) concept selection base c) learner performance measure (psychological and non-psychological) d) pedagogy flipping decision.

i. Tutoring Strategy Selection

The teaching of tutoring materials depends on numerous instructional strategies which can be interactively regulated by the instructor or teacher through the teacher interface. In a similar manner, the intelligent tutoring system decides the suitable instruction strategy for tutoring a concept/ subconcept contingent on some attributes (see Fig. 4). The attribute set comprises of features incorporated in learning materials as shown in table II and table III.

Table III Instructional strategy attributes

Attributes	Value		
	Value = 0	Value = 1	Value = 2
Learning Level	Beginner	Intermediate	Expert
Level of difficulty	Easy	Average	Tough
Category	In Depth, More detailed	Less detailed	Precise

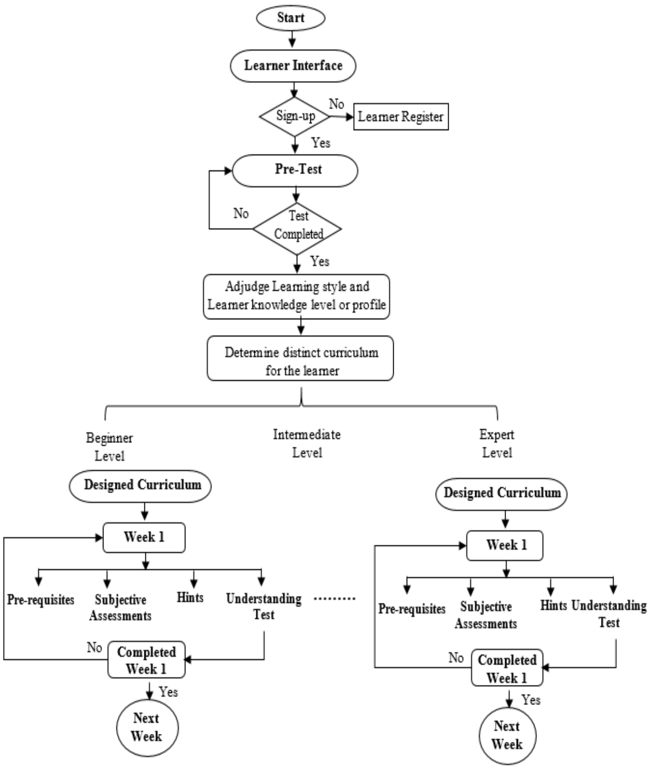

Figure 4 Course Overview

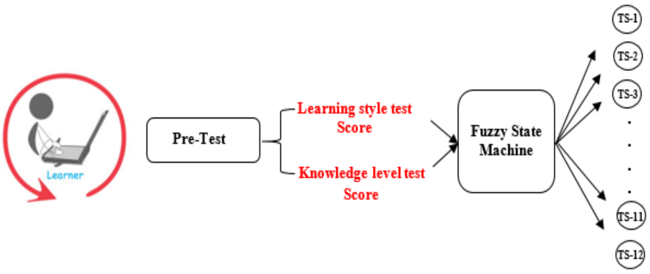

Figure 5 Flow diagram for Tutoring Strategy selection

The selection of suitable tutoring strategy is grounded upon the outcome of the pretest. As after pretest, Seis-Tutor having two test score, i.e. learner's learning style and knowledge level scores. Seis-Tutor apply soft computing technique (Fuzzy Logic) on these recorded scores.

This model comprises various states, where each state represents a tutoring strategy which is distinct from each other. Fig. 5 elaborates the steps involves in decision making. In this tutoring system more than one tutoring strategy is configured. For each strategy same transition model follows , thus the performance of the learner will not affect the decision making. Tutoring strategy is described as three tuple transition system, $\{TS, V, \delta\}$. Where,

- TS represents the Tutoring strategy states,
- V is the Input set, $v \in V$ *is a real number*,
- δ represents the transition function.

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The scope of this work considers only two parameters i.e. learning style score (LS) and knowledge level score (KL) which is recorded through pretest.
Therefore the current state of a learner is a combination of scores of two input set

$$V = (LS\ X\ KL) \quad (1)$$

Thus the composite state of V_i is consider as tuple $\{LS_i, KL_i\}$. The proposed fuzzy logic computes the tutoring strategy for the learner in linguistic terms.

$$Tutoringstrategy_i = \{TS1, TS2, TS3, TS4, TS5, TS6, TS7, TS8, TS9, TS10, TS11, TS12\}$$

Where,
TS1 is Active-Beginner,
TS2 is Active-Intermediate,
TS3 is Active-Expert,
TS4 is Acoustic-Beginner,
TS5 is Acoustic-Intermediate,
TS6 is Acoustic-Expert,
TS7 is Intuitive-Beginner,
TS8 is Intuitive-Intermediate,
TS9 is Intuitive-Expert,
TS10 is Imagistic-Beginner,
TS11 is Imagistic-Intermediate,
TS12 is Imagistic-Expert,

The benefit of representing the state of the learner in linguistic form is because it is easier and natural to comprehend for the learner and ease to deal with the uncertainty associated with these parameters.

Fuzzy State Computation

For leaner L, the state information is stored in the learner profile. At initial state the learner has not covered any topics successfully. The states of learner might be modified based on the performance in several assessment tests. For computing TS_x for the learner, SeisTutor consider two test score result which is saved in learner profile, *knowledge-level* (KL_l) and *learning-style* (LS_l). The test score value of KL_l and LS_l lie in [0, 20] and [0, 18] range respectively. Theses values are computed as soon as learner appears in a test just after he/ she register to the SeisTutor. When the SeisTutor records the value of KL_l and LS_l, the fuzzy state is computed. The fuzzy state computation for knowledge level is elaborated as follows.

$$v = \frac{KL_l}{2} \quad KL_l = [0-20] \quad (2)$$

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

$$\mu_{Beginner} = v \quad where\ 0 \le v < 3.5 \quad (3)$$

$$\mu_{Intermediate} = v \quad where\ 3.5 \le v < 7.0 \quad (4)$$

$$\mu_{Expert} = v \quad where\ 7.0 \le v \le 10 \quad (5)$$

Each questionnaire in learning style test having four options and each options is associated with I^{2}A^2 Learning style (*"Imagistic", "Intuitive", "Acoustic" and "Active"*). Thus, after learning style test the highest score value of learning style is elected or selected.
For example,
Let us consider a learner underwent learning style test and he overall score is stated in table IV.

Table IV Learning style test score

Imagistic	Intuitive	Acoustic	Active
5	2	9	2

Thus,

$$LS_l = \mu_{Acoustic}$$

There are total twelve tutoring strategy which is the permutation combination of LS_l and KL_l.

Table V elaborates the rules for tutoring strategy selection.

if knowledge_level is $\mu_{Intermediate}$ (4.5)
and learning_style is $\mu_{Acoustic}$ (9)
then, tutoring strategy is $acoustic\_intermediate$.

ii. Concept Selection Base.

Concept selection base as its name indicates, it is used to direct the SeisTutor to select the adjudged tutoring strategy. Concept selection base selects the concepts and subconcepts by referring or considering the outcomes of tutoring strategy and learner specific designed curriculum. Fig. 6 illustrates the steps followed by the concept selection base to incorporate the adaptability and custom-tailored features in SeisTutor. Concept selection base firstly retrieves the curriculum design and tutoring strategy outcomes. After receiving both the outputs, it passes the instruction to the domain model and retrieve the learning material from it. After gathering appropriate learning material from domain model it populates the learning material in tree form via learner interface as shown in figure 6. For better presentation, concept selection base, retrieves the meta-description of courses and concepts.

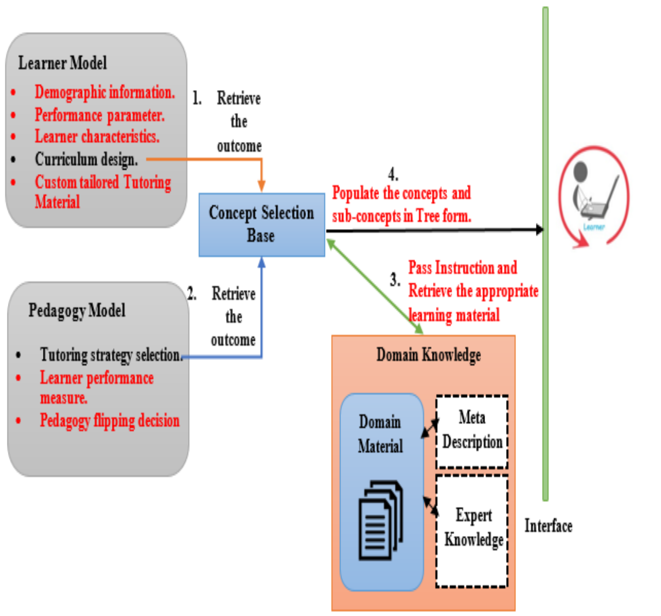

Figure 6 Flow diagram of concept selection base

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iii. Learner performance measure

Week-wise assessments test

This test comprises of 10 multiple-choice questions with four choices for each question. This test gets repeated after the completion of the week-wise concepts. This test comprises questions from the content. The types of questions in this test are direct answers, deep reasoning and assertion type questions. The responses to the question are recorded for further processing.

Degree of engagement measure (post questionnaire, emotion module)

The learner engagement measure is captured throughout the tutoring session by emotion capturing module and post week-wise engagement questionnaire. As soon as learner starts the week-wise plan emotion capturing module gets activated and after some pre-decided time interval (30 seconds) it capture the snap of learner via webcam and based on Facial Action coding System, psychological state of the learner is identified. According to Ekman et al there are total 46 action units which are responsible for expression change [18]. After completion of the week-wise concepts, the learner are determined by their affection state.

The Post week-wise engagement questionnaire required to ask the learner to self-mention their engagement level after the completion of the week-wise concepts. Three questions were asked to the learner to appraise their involvement or engagement during lecture with SeisTutor at beginning, intermediate and finish. Learner indicates they appraise on the six point likert scale from very bored to highly engaged.

Subjective measure (level of difficulty of tutoring material)

The subjective measure asked few questionnaires to the learner to appraise the tutoring concepts, measure of difficulty level, learner satisfactions, usefulness, understandability and effort. a)Difficulty level- "*how difficult did you find the tutoring concept is*" b) Learner satisfaction- "*how satisfy are you with the tutoring concept"* c) usefulness- "*how valuable did you find the tutoring concept is"* d) understandability- *"how easily you deduce the tutoring concept*" e) effort- *"how much effort you have to put in this tutoring concept to understand"*. Learner specifies their appraise on the six point Likert scale.

iv. Pedagogy flipping

As aforementioned Seis-Tutor captures various performance parameters during the week-wise assessments. After this assessments learner updates the learner, the profile's for future reference. As one can say with confidence that learner model is acting as a report card or blue print of the learner, which helps to understand, deduce conclusions, and helps to take necessary action to enhance the learning performance of learners. The learner profile is detailed with the help of numerous parameters. Seis-Tutor considers three aspects to determine the cognitive state of learner, namely *problem solving skill (PS), hint taken (HT)* and *incorrect response (IR). Problem solving* skill specifies the ability of the learner to understand the concept and apply the concepts for solving the problem, *hint-taken* specifies the assistant needed by the learner in understanding, solving the problem and *incorrect response* specifies where the learner is failing to apply the learned concepts accurately. The values of *PS, HT* and *IR* fall in the range [0-10]. These parameters define the learner aptitude. The learner profile is dynamic in nature because the values of these parameters get updated when learner appears for a week-wise assessments. Thus in a particular moment the <PS, HT, IR> pair indicates the learner's cognitive state. These values help SeisTutor to assess the learner profile, understand its psychological states and act accordingly. For brief understanding, let us consider an example, if a learner attained a low value for problem solving skill, and not taken SeisTutor assistant for solving the problem and have high incorrect responses, then SeisTutor ask the learner that is he or she is happy with the pedagogy or there is need to flip the pedagogical style. If yes, then SeisTutor flip the pedagogy, which is second best suited for the learner. Based on the aforementioned parameters for adjudging cognitive state of the learner SeisTutor decides the whether there is a need of pedagogy flipping or not. This information is recorded for further planning process. The learner performance measure is dynamic in nature. It keeps on changing whenever the learner underwent a week-wise assessments.

For each strategy same transition model follows , thus the performance of the learner will not affect the decision making. The cognitive state of learner, is described as three tuple transition system, $\{PF, W, \delta\}$. Where,

- PF represents the pedagogy flipping states,
- W is the Input set, $w \in W$ *is a real number*,
- δ represents the transition function.

The scope of this work considers only three parameters, i.e. *problem solving skill (PS), hint taken (HT)* and *incorrect response (IR),* which is recorded through the week-wise assessments.

Therefore the current state of a learner is a combination of scores of three input set

$$V = (PS \; X \; HT \; X \; IR) \qquad (6)$$

Thus the composite state of W_i is consider as tuple $\{PS_i, HT_i, IR_i\}$. The proposed fuzzy logic computes the cognitive state of the learner in linguistic terms, i.e. *("highly-effective" , "effective" , "improvement required")*. The benefit of representing the state of the learner in linguistic form is because it is easier and natural to comprehend for the learner and ease to deal with the uncertainty associated with these parameters.

Fuzzy State Computation

For leaner L, the state information is stored in the learner profile. At initial state the learner has not covered any topics successfully. The states of learner might be modified based on the performance in several assessment tests. For computing PF_x for the learner, SeisTutor consider week-wise assessment performance parameters score result which is saved in learner profile, *problem solving skill (*PS_i*),* *hint taken* (HT_l) and *incorrect response* (IR_l)The test score value of PS_l, HT_l and IR_l lie in [0, 10] range respectively. These values are computed as soon as learner appears in a week-wise assessment test just after finish the week-wise designed concepts.

When the SeisTutor records the value of PS_l, HT_l and IR_l the fuzzy state is computed. The fuzzy state computation for pedagogy flipping is elaborated as follows.

$$w = \frac{PS_l + HT_l + IR_l}{3} \quad W_l = [0 - 10] \qquad (7)$$

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

$$\mu_{Impr} = w \quad where\ 0 \le w < 3.5 \qquad (8)$$

$$\mu_E = w \quad where\ 3.5 \le w < 7.0 \qquad (9)$$

$$\mu_{he} = w \quad where\ 7.0 \le w \le 10 \qquad (10)$$

If the fuzzy state computation for pedagogy flipping is μ_{Impr} then SeisTutor triggers the message that "*SeisTutor detects for your performance that learner is not satisfied with the current Tutoring strategy thus Expert system recommends you to flip the pedagogy are you agree?*".

V. Experimental Analysis and Discussions

The SeisTutor was implemented and evaluated on graduation pursuing students of the university. Total 74 learner's willingly shown their interest to participate in this study. 74 learner's have been creating their SeisTutor account and gets a distinct Sap Id after registration they underwent Pretest. As aforementioned, there are two tests in Pretest (Learning style test and Knowledge level test). Table VI illustrates the demographic information of learner's. Out of 74 Participants 46 Participants are Male and remaining are female. 45% of participants lies in 20-22 age limit, 36 % of participants lies in 18-20 age limit and remaining lies in 22-24 age limit. All participants are pursuing graduate; thus their higher education is higher/ secondary schools.

Table VI Demographic Information of Learner's

Demographic Characteristics			
Characteristic		**N= 74**	
		Frequency	**Percentage**
Gender	Male	46	62 %
	Female	28	38 %
Age	18-20	27	36 %
	20-22	33	45 %
	22-24	14	19 %
	24-26	0	0 %
	>26	0	0 %
Education	Diploma	0	0 %
	High/ Secondary School	74	100 %
	Graduation	0	0
	Post-Graduation	0	0

The subject domain of implementing Intelligent Tutoring System SeisTutor is *"Basics of Seismic Data Interpretations"*. SeisTutor is designed and implemented to deliver tutoring concepts by following the architecture and methodology illustrated in section 2 , 3 and 4. The I^{2}A^2 learning style model is used for determining the learning style. Further fuzzy techniques are utilized for determining the appropriate tutoring strategy and curriculum. Then every learner proceeds with his or her respective determined tutoring strategies. Several performance parameters get captured by SeisTutor during entire tutoring sessions. Rules are predefined and get triggered , whenever the necessary steps are required to enhance the learning gain. Thus if SeisTutor detects that from the predicted tutoring strategy, there is no measurable learning gain, then in this case SeisTutor change the tutoring strategy which best suits the Learner profile and learning style.

This article discussed the experimental outcomes collated from two studies elaborated as follows.

Study 1: in this study the effectiveness and adaptability of SeisTutor is tested. Here learner for which SeisTutor detected to change the tutoring strategy in between the ongoing tutoring sessions.

Study 2: Here in this Study learner, who has shown the desirable learning gain from the predicted tutoring strategy is taken into the consideration.

Experiment 1:

As aforementioned in section 2, 3 and 4, that a post tutoring, assessment is performed after completion of every week. Thus SeisTutor captures both Pre-tutoring score as well as post-tutoring score of every week. A post tutoring and pre-tutoring score is normalized in range [0-10]. Further, these scores are used to compute the Learning Gain.

$$LG_l = \frac{(PostScore_L - PreScore_L)}{1 - PreScore_L} \qquad (10)$$

Utilizing above formula learning gain of a learner is computed. Table VII and Fig. 7 illustrates the comparative learning gain between the studies. An average learning gain of 74 learner is 13 %. The average learning gain is higher for study 1 15 %. This is may be due to the motivation factor of learners in completing and getting tutoring material as per their preferences and needs. The average learning gain for study 2 is around 13 %, thus a lower learning gain was anticipated because of distractions. Thus from the computed results of SeisTutor one can deduce that SeisTutor helps learners to enhance their learning of *"Basics of Seismic Data Interpretations"*.

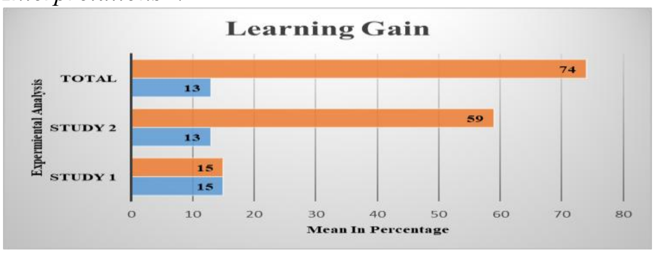

Figure 7 Learners Learning gain Results.

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Table VII Learning Gain Results

Study Cases	No of Participants (n)	Learning Gain		
		Mean (/10)	Standard deviation	Mean %
Study 1 : **Pedagogy change - Yes**	15	1.5267	.46209	15%
Study 2 : **Pedagogy change - No**	59	1.3169	.45454	13%
Total	74	1.3595	.46077	13%

Experiment 2:

As aforementioned section 2, 3 and 4, that other than Pretest and Posttest score SeisTutor also captures the other parameters like learner affections state or *emotion capturing* module (entire tutoring session) and *post week-wise engagement questionnaire*. During *post week-wise engagement questionnaire* SeisTutor wish to know the learner opinion about their engagement during the entire tutoring session. SeisTutor asked three questions to the learner to appraise their involvements during beginning, intermediate and at the end of the tutoring phase. Table VIII, Fig. 8 and 9 illustrates the comparable affection states and engagement levels between the studies.

Table VIII Learner Engagement Results.

Study Cases	No of Participants (n)	Parameters		Engagement Level		
				Mean (/10)	Standard deviation	Mean %
Study 1 : Pedagogy change – Yes	15	Affection State		3.4000	1.05560	34 %
		Engagements Levels	Beginning	0.333	0.61721	3 %
			Intermediate	2.0667	1.38701	20 %
			End	.8000	0.77460	8 %
Study 2 : Pedagogy change - No	59	Affection State		3.4746	1.10416	34 %
		Engagements Levels	Beginning	2.5593	1.80298	25 %
			Intermediate	.4407	.70151	4 %
			End	1.2881	.89155	12 %
Total	74	Affection State		3.4595	1.08778	34 %
		Engagements Levels	Beginning	2.4595	1.72959	24 %
			Intermediate	.4189	.68260	4 %
			End	1.1892	.88636	11 %

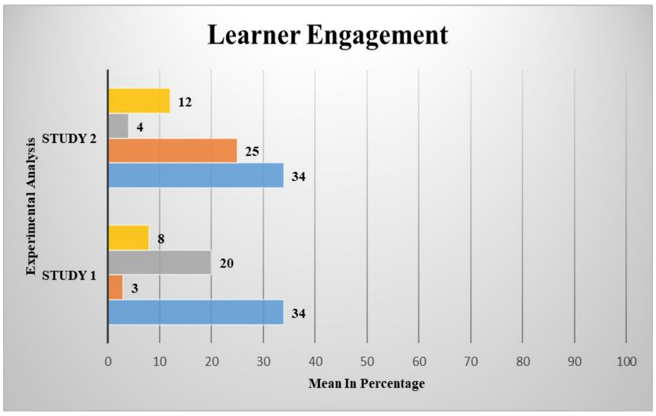

Figure 8 Learner Engagement Results

The average affection state is 34% and learner's finds to be highly engaged at the beginning 24 %, slightly dis-engaged in the middle of the tutoring session 4 % and again there in an improvement in engagement at the end of the tutoring sessions i.e. 11 %. The average affection state of study 1 is 34 % and learner finds to be highly engaged at the middle of the tutoring session 20 %. The average affection state of study 2 is 34 % and learner finds to be highly engaged at the beginning and end tutoring sessions i.e. 25 % and 12 % respectively. In affection state module SeisTutor captures the cognitive state of the learner. Out of 46 affection states SeisTutor captures 5 affections states, i.e. *"Surprise", "Smile", "Neutral", "Sad"* and *"Ambiguous"*. Table IX describes the comparable affection state of learner's captures between studies. A similar result patterns have been captured in both the studies. The average affection state in study 1 is neutral 40 %, smile 33.3 % , surprise 13.3 %, sad 6.7 % and ambiguous 6.7 %. While in study 2 neutral 33.9 % , smile 28.8 % surprise 20.3 %, sad 11.9 % and ambiguous 5.1 %.

Table IX Affection state Results

Study Cases	No. of Participants (n)	Affection States	N= 74	
			Frequency	Percentage
Study 1 : **Pedagogy change – Yes**	15	Surprise	2	13.3 %
		Smile	4	33.3 %
		Neutral	6	40.0 %
		Sad	1	6.7 %
		Ambiguous	1	6.7 %
Pedagogy change - No	59	Surprise	12	20.3 %
		Smile	17	28.8 %
		Neutral	20	33.9 %
		Sad	7	11.9 %
		Ambiguous	3	5.1 %

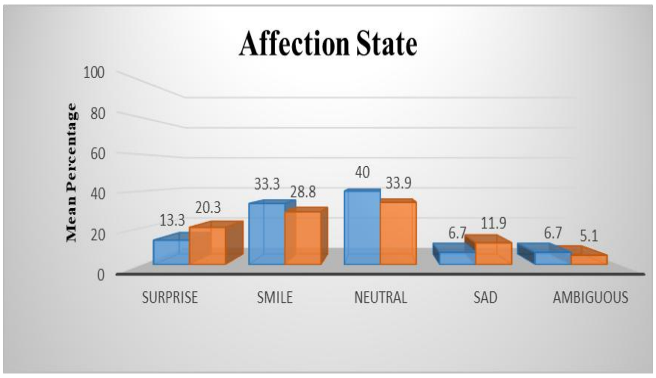

Figure 9 Learner Affection state during tutoring session

Experiment 3:

As illustrates in aforementioned sections 4, that SeisTutor wish to know the learner opinion on the tutoring concepts measure of difficulty level, learner satisfactions, usefulness, understandability and effort. Thus, SeisTutor asked some questions to the learner to appraise their opinion on the range of six Likert scale. Table X illustrates the comparable subjective measure between the studies. An interesting opinion of learner is determined, computed, and explained in table X and Fig. 10 and Fig. 11. The learner in study 1 finds the difficulty level of tutoring material is 20 %,

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their satisfaction percentage is 15, the usefulness of tutoring material is 20 % and the degree of understandability and effort is 16.6 %.

While the learner in study 2 finds the difficulty level of tutoring material is 25 %, their satisfaction percentage is 12, the usefulness of tutoring material is 24 % and the degree of understandability and effort is 16 % and 14 % respectively.

Table X Subjective Measure Results

Study Cases	No of Participants (n)	Parameters	Subjective Measure Mean (/10)	Subjective Measure Standard deviation	Subjective Measure Mean %
Study 1 : **Pedagogy change – Yes**	15	Difficulty Level	2.0667	1.3870	20 %
		Learner Satisfaction	1.5432	.86474	15 %
		Usefulness	2.0667	1.3870	20.0 %
		Understandability	1.6667	.89974	16.6 %
		Effort	1.6667	1.49603	16.6 %
Study 2 : **Pedagogy change - No**	59	Difficulty Level	2.5593	1.8029	25 %
		Learner Satisfaction	1.2831	.88854	12 %
		Usefulness	2.4371	1.7129	24 %
		Understandability	1.6780	1.30570	16 %
		Effort	1.4915	1.20877	14 %

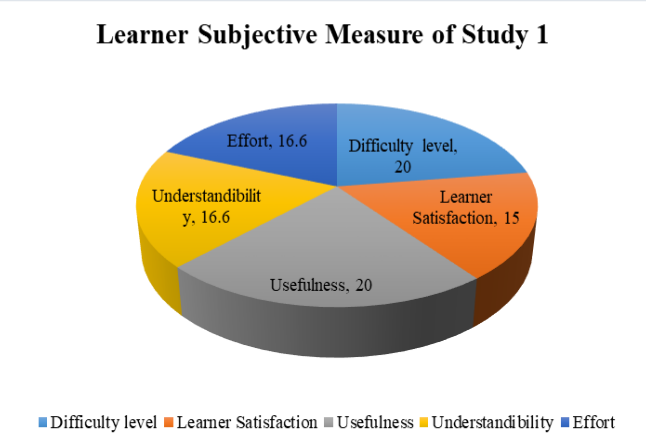

Figure 10 Learner subjective measure of study 1

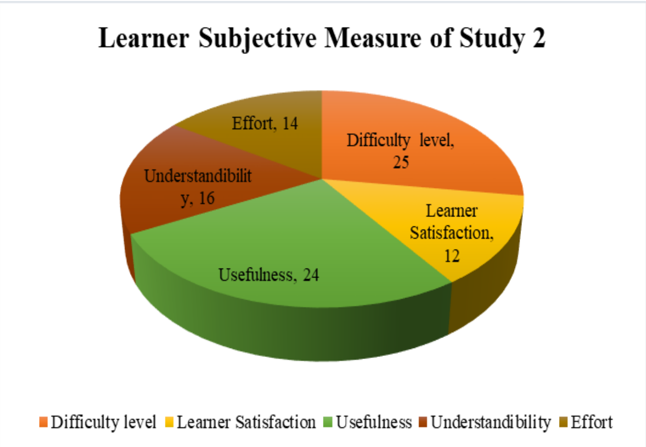

Figure 11 Learner subjective measure of study 2

VI. Conclusion

This article briefly explained the SeisTutor architecture, which not only implicitly determines the learning style, but also determine the pre knowledge level prior to beginning the tutoring sessions. This novel architecture imitates the human cognitive intelligence of adaptability, understandability by designing a distinct exclusive curriculum sequencing and tutoring strategy before beginning the tutoring session. A tutoring concepts are directed through SeisTutor which capture the affection states and others performance parameters from the post assessment test, post week-wise engagement questionnaire and subjective measure. Based on the performance parameters SeisTutor decides to flip the tutoring strategy when appropriate learning gain is not received. SeisTutor provides a personalized learning environment help to enhance the confidence and learning gain. Implemented SeisTutor was empirically evaluated on graduation pursuing learners. The analysis discloses that learning style model were accurately predicted with an accuracy of 61-100 %. The applicants found SeisTutor is helpful with an average of 13 % learning gain, attains 24 % engagement during tutoring session.

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