“A LEARNER-CENTRIC KNOWLEDGE-BASED TUTORING ENGINE WITH DYNAMIC PROFILING AND PEDAGOGICAL RECOMMENDATION FOR SEISMIC DATA INTERPRETATION”

A thesis submitted to the
University of Petroleum and Energy Studies

For the award of
Doctor of Philosophy
in
Computer Science and Engineering

BY
Ninni Singh

Aug 2020

SUPERVISOR
Dr. Neelu Jyothi Ahuja

School of Computer Science
University of Petroleum and Energy Studies
Dehradun-248007; Uttarakhand

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DECLARATION

I declare that the thesis entitled **"A Learner-Centric Knowledge-Based Tutoring Engine with Dynamic Profiling and Pedagogical Recommendation for Seismic Data Interpretation."** Has been prepared by me under the guidance of Dr. Neelu Jyothi Ahuja Professor of Computer Science University of Petroleum and Energy Studies, Dehradun. No part of this thesis has formed the basis for the award of any degree of fellowship previously.

Ninni Singh
School of Computer Science
University of Petroleum and Energy Studies
Dehradun,
Date: 16th March 2021

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CERTIFICATE

I certify that Ninni Singh has prepared her thesis entitled **"A Learner-Centric Knowledge-Based Tutoring Engine with Dynamic Profiling and Pedagogical Recommendation for Seismic Data Interpretation."** For the award of PhD degree of the University of Petroleum and Energy Studies Dehradun, under my guidance. She has carried out the work at the School of Computer Science, University of Petroleum and Energy Studies.

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ABSTRACT

Artificial Intelligence is an advanced field of research. It is particularly used in the field of education to increase the effectiveness of teaching and learning techniques. Ongoing research and development initiatives have led us to the origin of intelligent tutoring. It has gained immense popularity in current times specifically due to the development of Intelligent Tutoring Systems (ITS). In the early twentieth century, the Intelligent Tutoring Systems are/were termed as the most prevalent and effective way to learn and teach. However, there exist some traditional comparative studies that depreciate these artificial teaching and learning techniques. The current scope of the work focuses on Pedagogy and Domain models of ITS. The aim of this research is to develop an adaptive tutoring engine, facilitating, knowledge base delivery through a learner-centric learning path. The domain knowledge incorporated in the proposed Intelligent Tutoring System is Seismic Data Interpretation (SDI). The proposed ITS has been named as SeisTutor.

SDI involves a set of steps outlining the procedure in which a given seismic snap (image) depicting the subsurface geology is interpreted. The main purpose of this is to discover geological structures appropriate for hydrocarbon amassing. Being in the process of interpreting seismic images over several years, the seismologists are very well-versed and have uncovered many less-known or unknown details. This knowledge is large, experiential, and individualistic in nature, and it is present in minds of Experts. Thus, it is present in tacit form, and not in explicit form. Till date, there are no efforts known to make this knowledge explicit and further use it to teach to novice seismologists. There are various mechanisms to explicating the tacit knowledge. In the present work, initially causal map mechanism was used, a series of questions were put forward in two phases in independent settings and gathered knowledge was used for developing the causal map. The second phase of the work was initiated with semi-structured mechanism, with the same subjects (seismologists) and same researcher teams, as in phase 1. The results were cumulated and a formal account of each topic of interest was generated. This led to the construction of a knowledge capsule, which was an explicit representation of knowledge.

After extraction of knowledge, the next challenge is to transform it into a form which could be utilized for tutoring. The procedure followed was to sequence and classify the gathered knowledge as per seismologist's guidelines and the degree of tacit-ness (td). The term tacit-ness (td) can be defined as the extent to which a given piece of knowledge is tacit and undocumented. After validating the sequenced knowledge through ongoing consultation with seismologists, knowledge capsules or individual units of knowledge have been developed. The knowledge capsule is made available to novice seismologists in different imbibing levels and preferred media. The current scope is limited to offering three learner grasping levels ('*Beginner*', '*Intermediate*', '*Expert*') and four preferred media ('*Imagistic*', '*Intuitive*', '*Auditory*', '*Active*'), adding up to twelve different types of combinations. The learner dashboard forms an interactive interface to deliver the knowledge capsule as learning material, (subject matter of seismic data interpretation) in twelve distinct manners, offering the learner a customized learning experience.

Under the current scope of work, implementation of adaptive tutoring strategy is done by making use of learner's 'prior knowledge level' and a curriculum is offered accordingly. Custom-tailored curriculum has been implemented and made available to the learner based on 'Bug Model'. The present research work is focused on a well-planned, systematic start of the tutoring process, doing so by a curriculum design suitable for a given learner which presents a navigable learning path. To evaluate the effectiveness of the learning process, two analysis modules were designed and developed, one is CNN based psychological states recognition module and the other is performance analyzer module. Currently, the recognized psychological states are being used for the purpose of keeping track of learner emotions during the ongoing tutoring. This is the input to the dynamic profiling of learner, over ongoing tutoring. This mechanism has been implemented using Machine Learning Techniques of Artificial Intelligence. This code snippet accepts input, an individual learner's snap during ongoing tutoring session and recognizes the psychological states (*"Happy", "Sad", "angry", "surprise", "fear", "disgust", "neutral")*. Then these are displayed along with the learner progress. The tutoring sessions are aligned and executed in a week-wise pattern. After every first week, a performance analyzer module (subjective test) has been implemented. This test prompts the learner to summarize the understanding of provided learning content in the form of plain text.

The evaluation of SeisTutor is performed with total 60 learners from an academic background of petroleum engineering. Out of 60 learners, 32 learners are categorized as a control group and remaining 28 learners as the experimental group. The experimental set-up was laid up for an evaluation study. The aim of evaluation is assessment of level of effectiveness gained at achieving learning objectives. In post tutoring phase, two widely accepted methods were used: The analysis of learner performance and a well-accepted Kirkpatrick Model. To evaluate learning performance, the ANOVA test is conducted with scores of participants in pretest and posttest tests, which is a well-known method for assessing the effectiveness of training program. The results indicate the significant difference in outcome achievement quantified by learning gain of 44.4%.

Kirkpatrick's Four Levels Evaluation Model is another widely accepted method for evaluating the effectiveness of training for a variety of organizational types (Kirkpatrick & Kirkpatrick, 2006). The levels are: 1-Reaction, 2-Learning, 3-Behavior, and 4-Results. The outcome of "Reaction" reveals that, 44 % learners are happy with the offered learning content (customized learning content) and teaching process i.e. pedagogy. The outcome of "Learning" reveals that, the experimental group showed 44.4 % of learning gain as against a control group with only 24.8%. This is indicative that, experimental group of SeisTutor experienced enhanced learner interest and curiosity, indirectly relatable to increase in the learner performance. The outcome of "Behaviour" reveals that, the proposed system design produces productive learning in the domain of SDI through the application of computer science and artificial intelligence. In addition, the 86% learners were satisfied and achieved better results with SeisTutor and improved learning due to the use of Custom-Tailored tutoring strategies. The outcome of "Results" indicates that the calculated T value (T_{Stats}) for the experimental group is 11.410, $P < 0.01$. The average posttest scores were 2.21786 points higher than pretest scores. Here the calculated T_{Stats} is greater than $T_{critical}$ thus hypothesis 1.0 (negligible performance improvement) is rejected. Therefore, one can deduce with confidence that the experimental group has gained effective learning as against the control group. A comparison of SeisTutor with the existing open-source e-learning software is presented and evaluated based on the parameters like GUI based, Learner-Centric learning environment, dynamic profiling, learning content, resolving query during the session, navigation support, and learner feedback. The conclusion drawn from this comparative analysis is that 74 % of learner are strongly satisfied with the SeisTutor ('GUI based', 'Learner-

Centric Learning Environment', 'Dynamic Profile', 'Learning Content', 'Resolving Learner Query during Session', 'Navigation Support', and 'Learner Feedback').

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I would like to thank my parents for their constant support and love at every stage of my life. Completing this degree would never be possible without their love and encouragement. Finally, a gratitude to all my dear colleagues for their continuous help and support.

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Keyword for Week 1

Main Reference Matric	N-gram Co-Occurrence Matric	Labels
Petroleum Exploration	Four	Basic Stages
	Seismic acquisition, Seismic data processing, Understanding the data and Seismic data interpretation	Stage classification
Seismic data Processing	Various seismic gathers	Types of analysis
	Common midpoint binning	Types of analysis
	Stacking	Types of analysis
Seismic Waves	Sudden breaking of rocks	Reason of occurrence
	Two types	Classification
Body waves	Primary waves	Classification types
	Secondary Waves	Classification types
Surface waves	Rayleigh waves	Classification types
	Love waves	Classification types
Primary waves	Compressional waves	Wave motion
	Fastest waves	Speed
	Solid and liquid	Can move
Secondary Waves	Transverse wave	Wave motion
	Medium	Speed
	Solid	Can move
Rayleigh Waves	Rolls	Wave motion
	Slow	Speeds
	Earth surface	Can travels
Love Waves	Side to side	Wave motion
	Fastest	Speeds
	Earth surface	Can travels
Velocity	Reflection	Change result
	Refraction	Change result

Keyword for Week 2

Main Reference Matric	N-gram Co-Occurrence Matric	Labels
Seismic Sources	Marine	Acquisition
	Land	Acquisition
Land Acquisition	Explosives	Technique used
	Thumper Truck	Technique used
	Vibroseis	Technique used
Marine Acquisition	Airgun	Technique used
Explosives	Drill Hole	Perform by
	Chemical composition	Made up of
	Cheap	Cost
Thumper Truck	Vibrator	Process
	seismic waves	Emit
Vibroseis	Vibrator	Process
	seismic waves	Emit
Airgun	pneumatic chambers	Consist of
	Air	Release
Seismic Receivers	Marine	Acquisition
	Land	Acquisition
Land Acquisition	Geophone	Technique used
Marine Acquisition	Hydrophone	Technique used
Geophone	Electric voltage	Produce
	Coil and magnet	Relative motion
Hydrophone	Change	Detect
	Pressure sensor	Compasses tail bouys
Analog Recording	Analog amplifier	Analog to digital converter process
	Analog filter	Analog to digital converter process
	Magnetic analog recorder	Analog to digital converter process
	Continuous	Signals form
Analog amplifier	Automatic gain control	Special circuit
Analog filter	Noise	Remove
Magnetic analog recorder	Modulators	Seismic range
Horizon	Contouring	Steps involve
	Well-Calibration	Steps involve
	Velocity Estimation	Steps involve
	Depth map	Steps involve
Contouring	Three dimensional form	Representation of horizon
Well-Calibration	Two way travel time to depth	Conversion
Velocity Estimation	Migration	Seismic Imaging

Depth map	Structural ambiguity	Used to remove

Keyword for Week 3

Main Reference Matric	N-gram Co-Occurrence Matric	Labels
Faults	Foot wall	Walls
	Hanging wall	Walls
	Normal faults	Types
	Reverse faults	Types
	Strike slip faults	Types
	Stress	Reason of breaking
Normal faults	Divergent	Plate motion
	Tension	force
Reverse faults	Convergent	Plate motion
	Pushing	force
Strike slip faults	Transform	Plate motion
Stress	Tensile	Types
	Compressive	Types
	Shear	Types
Strain	Tensile	Types
	Compressive	Types
	Shear	Types
	Volumetric	Types

Keyword for Week 4

Main Reference Matric	N-gram Co-Occurrence Matric	Labels
Direct Hydrocarbon Indicators	Flat spot	Types
	Bright Spot	Types
	Dim Spot	Types
Velocity Interpretation	Average	Types
	Interval	Types
	Root Mean Square	Types
Faults map	Understanding	Uses
	Drilling plan	Uses
	Location	Uses
2D	Less data	Survey
3D	Data	Survey

Appendices 2

Table 7.15 Learner Feedback on effectiveness of SeisTutor

	Questions	Degree				
		Strongly satisfy	**Satisfy**	**Neutral**	**Dissatisfy**	**Strongly dissatisfy**
System Effectiveness	What is your overall level of satisfaction with SeisTutor?	27	23	6	3	1
	The learning through this tutoring system (SeisTutor) was easy.	27	26	5	1	1
	Did you feel that you were achieving learning outcomes?	30	21	6	3	0
	I would recommend a course through SeisTutor with no instructor help	29	24	3	5	0
	Would you recommend SeisTutor to individual who needs to take another course?	25	27	5	3	0
	Did SeisTutor support you to make your study productive?	28	27	3	0	2
	How well does this system deliver on your learning intentions?	31	21	5	2	1

Table 7.16 Learner Feedback on Adaptivity of SeisTutor (Adaptive Tutoring Strategy)

	Questions	Degree				
		Strongly Satisfy	**Satisfy**	**Neutral**	**Dissatisfy**	**Strongly dissatisfy**
Adaptivity /	Did SeisTutor satisfy you with dynamic creation of your learning profile?	27	21	7	1	4
	Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor?	24	19	9	6	2
	The information provided by SeisTutor is at a level that you understand.	29	17	12	0	2

	The tutoring session was at the right level of difficulty for you.	26	23	9	2	0
	As a learner, did you feel that your learning style was appropriately judged?	29	25	3	2	1
	Once, tutoring begins and you were tutored, were your learning preferences sufficiently satisfied?	24	24	9	2	1
	Did the experience of learning by your own learning preference, make you perform better?	24	21	6	7	2
	Based on your prior subject knowledge, has SeisTutor accurately determined exclusive curriculum for you?	14	8	2	3	1
	How satisfied are you with the exclusively determined curriculum?	13	7	4	3	1
	As a learner did you feel learning material enabled you to improve your ability to formulate and analyse the problem?	10	14	1	3	0
	Are you satisfied with the sequencing of learning content?	14	09	3	2	0
	Does sequencing of learning material relate with your previous knowledge? (Give Rating)	12	11	2	3	0
	Has this learning session been successful in improving your knowledge in the subject domain? (Give Rating)	12	11	2	3	0
	Did this learning material fulfill your expectations?	11	13	2	1	1
	The Understanding Test at the end of each week corresponds to the lessons taught?	11	13	2	0	2
	Seis Tutor compels and supports me to complete the quizzes , understanding test and lessons ?	13	12	2	0	1

	The Post Tutoring Evaluation system (Week Wise Understanding) as it exists is :	14	10	1	2	1
	How do you rate the sequence of the lessons in the course?	18	8	0	0	2
	Has Seis Tutor accurately determined your psychological (Emotional) state during tutoring session? (Give Rating)	11	7	5	5	0
	Do you feel recognition of emotion during ongoing tutoring is indicative of empathy of the system?	13	12	2	0	1
	The course content are relevant and well organized ?	14	10	1	2	1

Table 7.17 Learner Feedbacks on SeisTutor ongoing Learning Support

Questions	**Degree**				
	Strongly Satisfy	**Satisfy**	**Neutral**	**Dissatisfy**	**Strongly dissatisfy**
How are you satisfied with the system support?	24	17	11	6	2
The system navigation support enabled finding the needed information easily.	21	17	9	11	2
Was the pre-learning procedure available in SeisTutor helpful to you?	25	17	6	9	3
Were you able to understand the language used to explain the lessons in SeisTutor?	33	21	6	0	0
The tutoring was flexible to meet my learning requirements.	30	21	7	2	0

Table *7.18* Learner Feedbacks on learning material, quizzes and overall SeisTutor support

Questions	**Strongly Satisfy**	**Satisfy**	**Neutral**	**Dissatisfy**	**Strongly dissatisfy**
SeisTutor explained the content correctly.	23	25	3	8	1
SeisTutor made the course as interesting as possible.	31	19	9	1	0

The tutoring resources were adequate.	21	19	7	9	4
The presentation of course content stimulated my interest during learning session.	32	24	2	1	1
The course content are relevant and well organized.	29	25	3	2	1
SeisTutor supported me to understand the content, which found confusing?	27	26	6	1	0
The quiz at the end of each week corresponds to the lessons taught?	28	27	3	1	1
The question wise hints were helpful.	27	26	6	0	1
Did the SeisTutor react decidedly to your necessities?	26	21	11	1	1
Was the learning provided sufficiently to take the quiz?	36	18	4	2	0
During ongoing tutoring, assessments are a fair test of my knowledge and learning preferences.	32	21	5	2	0

Appendices 3

Table 7.23 Learners Feedbacks on learning through My-Moodle

	Questions	Strongly-Dissatisfied	Neutral	Strongly-Satisfied
1	How satisfied are you with the look and feel (user interface design) of this system?	17	21	32
2	The Pre Tutoring Test is conducted	25	13	32
3	As a learner, did you feel that your learning style was appropriately judged?	32	20	18
4	The information provided by My-Moodle is at a level that you understand.	31	9	30
5	Were you convenient and satisfied with the tutoring strategy presented to you by My-Moodle?	25	10	35
6	Based on your prior subject knowledge, has My-Moodle accurately determined exclusive curriculum for you?	33	12	25
7	The course content are relevant and well organized.	35	25	10
8	Is My-Moodle accurately determined your psychological (Emotional) state during tutoring session? (Give Rating)	25	3	42
9	The Understanding Test at the end of each week corresponds to the lessons taught?	35	10	25
10	The Post Tutoring Evaluation system (Week Wise Understanding) as it exists is :	24	23	23
11	The system navigation support enabled you to find the needed information.	15	19	36
12	Is My-Moodle Handle the Learner's Issue/ during the ongoing Learning Session	37	9	24
13	Is My-Moodle gathers the Learner Valuable Feedback	23	10	37

Table 7.24 Learners Feedbacks on learning through Course-Builder

	Questions	Strongly-Dissatisfied	Neutral	Strongly-Satisfied
1	How satisfied are you with the look and feel (user interface design) of this system?	16	22	32
2	The Pre Tutoring Test is conducted	65	5	0
3	As a learner, did you feel that your learning style was appropriately judged?	50	18	3
4	The information provided by Course-Builder is at a level that you understand.	63	4	3

5	Were you convenient and satisfied with the tutoring strategy presented to you by Course-Builder ?	65	4	1
6	Based on your prior subject knowledge, has Course-Builder accurately determined exclusive curriculum for you?	56	9	5
7	The course content are relevant and well organized.	56	3	11
8	Is Course-Builder accurately determined your psychological (Emotional) state during ongoing tutoring session? (Give Rating)	61	7	2
9	The Understanding Test at the end of each week corresponds to the lessons taught?	61	7	2
10	The Post Tutoring Evaluation system (Week Wise Understanding) as it exists is :	4	12	54
11	The system navigation support enabled to find the needed information.	27	8	35
12	Is Course-Builder Handle the Learner Issue/ Problem during the ongoing learning Session	44	6	20
13	Is Course-Builder gathers the Learner Valuable Feedback	27	11	32

Table 7.25 Learners Feedbacks on learning through Teachable

	Questions	**Strongly-Dissatisfied**	**Neutral**	**Strongly-Satisfied**
1	How satisfied are you with the look and feel (user interface design) of this system?	1	30	39
2	The Pre Tutoring Test is conducted.	66	4	0
3	As a learner, did you feel that your learning style was appropriately judged?	47	18	5
4	The information provided by Teachable is at a level that you understand.	67	1	2
5	Were you convenient and satisfied with the tutoring strategy presented to you by Teachable ?	65	3	2
6	Based on your prior subject knowledge, has Teachable accurately determined exclusive curriculum for you?	63	5	2
7	The course content are relevant and well organized.	65	3	2
8	Is Teachable accurately determined your psychological (Emotional) state during tutoring session? (Give Rating)	66	1	4
9	The Understanding Test at the end of each week corresponds to the lessons taught?	39	28	3

10	The Post Tutoring Evaluation system (Week Wise Understanding) as it exists is :	12	13	45
11	The system navigation support enabled to find the needed information.	18	10	42
12	Is Teachable Handle the Learner Issue/ Problem during the ongoing learning Session	39	4	27
13	Is Teachable gathers the Learner Valuable Feedback	18	7	45

Table 7.26 Learners Feedbacks on learning through SeisTutor

	Questions	**Strongly-Dissatisfied**	**Neutral**	**Strongly-Satisfied**
1	How satisfied are you with the look and feel (user interface design) of this system?	11	10	50
2	The Pre Tutoring Test is conducted	6	5	59
3	As a learner, did you feel that your learning style was appropriately judged?	11	5	55
4	The information provided by SeisTutor is at a level that you understand.	13	6	52
5	Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor?	8	3	60
6	Based on your prior subject knowledge, has Seis Tutor accurately determined exclusive curriculum for you?	8	4	58
7	The course content are relevant and well organized.	12	4	55
8	Is SeisTutor accurately determined your psychological (Emotional) state during tutoring session? (Give Rating)	8	7	55
9	The Understanding Test at the end of each week corresponds to the lessons taught?	4	5	62
10	The Post Tutoring Evaluation system (Week Wise Understanding) as it exists is :	6	3	61
11	The system navigation support enabled to find the needed information.	14	8	48
12	Is SeisTutor Handle the Learner Issue during the ongoing learning Session	16	6	48
13	Is SeisTutor gathers the Learner Valuable Feedback	10	15	46

Chapter 1 Introduction

In this chapter introduction, problem statement, need and motivation, gaps, questions and scope of research have been discussed. Subsequently, the objectives of research, contribution, and organization of the thesis have been presented.

1.1 Introduction

The incorporation of Artificial Intelligence (AI) techniques into the field of education, makes learning and teaching more effective. In the recent past, this area has been rigorously exploited and has resulted in incremental growth in the development of numerous computer artifacts. There are various forms of computer artifacts, one amongst are Intelligent Tutoring System (ITS) [1]. ITS field has originated at the intersection between three disciplines, i.e. Psychology, Computer Science and Education (shown in Figure 1.1). Psychology involves the study of learner behavior during interaction with the tutoring system. Computer Science covers the use of digital technology, in ITS, supporting the emulation of cognitive intelligence, and abilities of human tutors. The education covers the collection of knowledge and its delivery mechanism to the targeted learner.

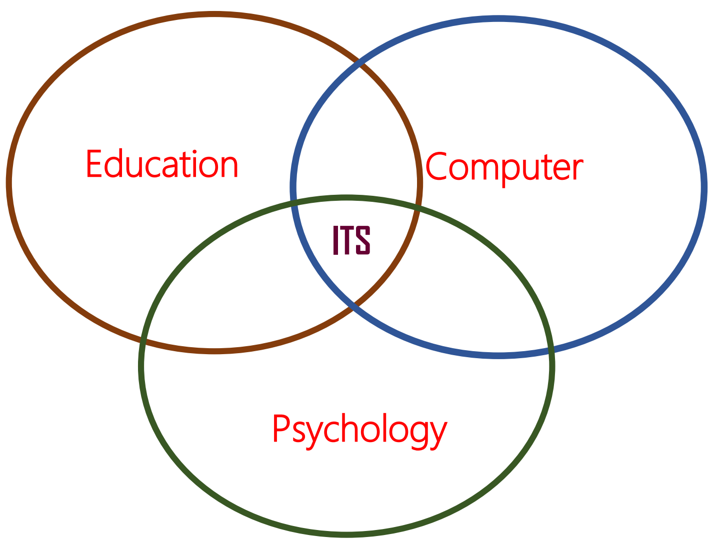


Figure 1-1 Intersection of disciplines leading to the birth of an Intelligent Tutoring System

Research in psychology, education, and computer science (AI and Machine Learning) fueled the foundation of the field of Intelligent Tutoring Systems. Thus, ITS aims to cognize the learner's needs, and grasping levels, offer the learning material that best suits the learner's requirements. ITS act as a cognitive tutor that not only solves the learner's issues (hints and feedbacks) but also keeps an eye on the learner's performance and activity during learning and deduces the competency level of learner's in the particular subject domain. It seeks to determine the learner's cognitive state of mind. Thus, identification of the cognitive state of learners makes a computer-assisted learning system an intelligent tutoring system. There is progressive growth of a computer-assisted learning system to various forms of web-based learning systems and a further advancement to form a personalized tutoring system.

There is a considerable difference between ITS and other web-based learning systems. A web-based learning system facilitates the learner to follow a specific learning material aligned in certain sequence same for all learners, hence fails to provide personalized learning environment and necessary personal guidance (hints and feedbacks) during learning.

Numerous ITSs/E-learning systems exist in the literature, with their distinct architecture (Wenger, 1986[2]; Baffes & Mooney, 1996[3]; Chou et al., 2003[4]; Conati et al., 2002[5]; [6]; [7]Kavcic et al., 2003; [8]). The architecture of a typical ITS is comprised of five main components: Learner Model, Pedagogy Model, Expert Model, Knowledge/Domain Model, and Learner Interface Model (see Figure 1.2).

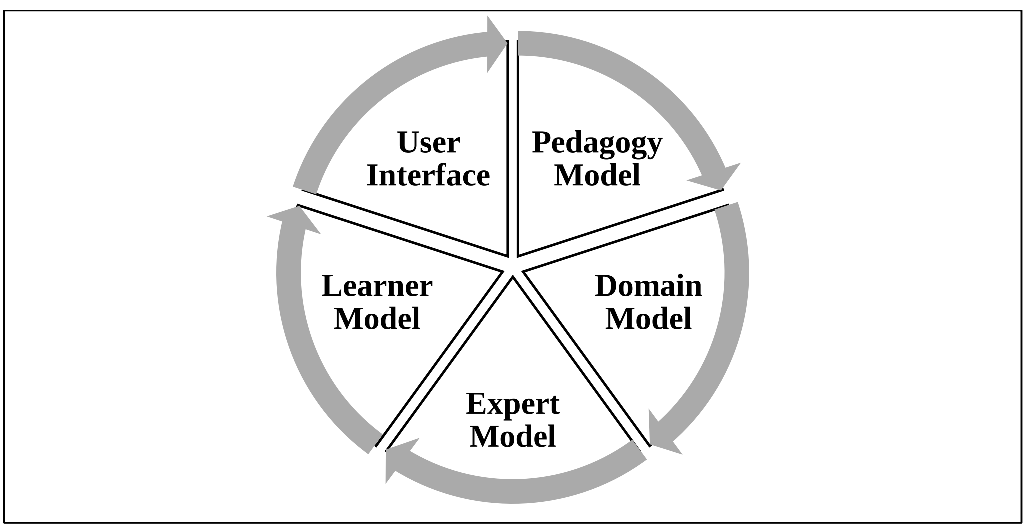


Figure 1-2 Architecture of Typical ITS

1. *Learner Model* captures the information about the learner, like their previous knowledge, Learning Style, errors, misconceptions (Freedman et al., 2000) [9]. It also stores the learner action and performance during learning (such as correct responses, the hint opted, incorrect responses)

2. *Pedagogy Model* responsible for making a strategic decision based on learner actions, the information provided by the Learner Model and Domain Model. This model first refers to the learner information from the Learner Model and identifies the appropriate pedagogical style based on learner preferences (profile and Learning Style) (Beck, J.E. & Chang, K.M. (2007) [10].

3. *Expert Model* uses share snippets of knowledge instructed to the learner. This model uses the knowledge, skills shared by the expert and represents the domain knowledge in such a way that helps to improve the problem-solving skills.

4. *Domain Model* holds knowledge or information being instructed by ITS. Knowledge from experts is represented in it in variety of forms. Facts and procedure are one way of representation.

5. *User Interface* model allows a learner to communicate with the learning system. This model amalgamates the interactive media and graphics to communicate with the learner.

Till now, various ITSs have implemented different subject domains such as physics, mathematics, computer science, and medical informatics. From the literature, it has been noticed that the domain knowledge in the developed ITS is of well-documented domains, i.e. Electrodynamics, Physics, SQL, C++, Physiology for Medical Students, Natural Language, English, Java, Maths and database (Virvou, M.et.al, 2004 [11]; [12]; [13]; [14]Vicari et al., 2008 [8] Mitrovic, 2003 [15]; Baffes & Mooney, 1996 [3]; Khuwaja et al., 1994 [16]; Naser, S. S. A., 2008 [17]; Chien et al., 2008 [18]). Till now there is no such ITS where domain knowledge is based on domains that are not well-documented, i.e. not available in explicit form, i.e. experiential knowledge.

Experiential knowledge is knowledge acquired through experience. More precisely, it is elaborated as "learning gained through activity." It is a process by which one can develop values and skills from experiences (see Figure 1.3). It relates to action learning, adventure learning, cooperative learning, and active learning.

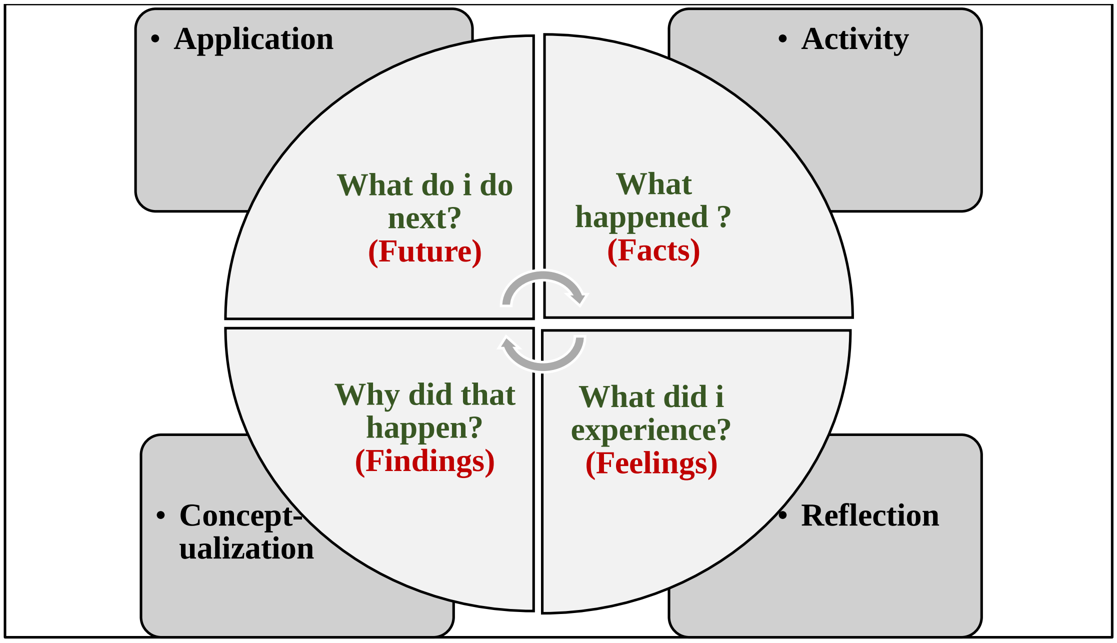


Figure 1-3 Features of Experiential Learning

In this research, *"Seismic Data Interpretation"* is the subject domain that is a type of experiential learning. Seismic Data Interpretation (SDI) is the field of Geophysics that falls under petroleum exploration processes. In the exploration process, seismologists (specialized scientists) outline the earth's subsurface structure using seismic SEG-Y Map. The seismologists use their knowledge to interpret the subsurface structure helpful to infer the presence of hydrocarbons. The interpretation task is difficult; hence more time is spent to come to a decision with appropriate justification. Due to a lack of evidences, it is difficult to convince other seismologists. Thus, there is uncertainty in the conclusions drawn by the seismologists. This uncertainty is due to the lack of thumb rules. Seismologists gain the interpretation skills with rigorous hands-on practice. Thus, this knowledge is experiential and highly individualistic. Therefore, SDI is considered as tacit knowledge.

A considerable amount of research work has been done and is continuing, in technologies that can improve the adaptation process in e-learning systems, including curriculum sequencing techniques and cognizing the psychological state of the learner. In a learning system, the classification of learning contents and its associated activities, and presenting to the learner to attain the learning goals is known as learning path. This learning path may differ from individual to individual, depending on his/her profile. This will give a different learning experience to every learner, further helps to grasp the learning content effectively. Every learner holds previous knowledge about the course subject. Thus, from the literature, it is deduced that if learning content is offered as per the learner's previous knowledge and preferences, there is an enhancement in overall learning and learner engagement. The notion of curriculum sequencing is to create a personalized course for each learner by automatically selecting the most suitable teaching format, such as presentation slides, video lectures, audio lectures.

An adaptive intelligent tutoring system incorporates the learner's emotions along with the personalization. For instance, in Wolcott [19], it is argued, human tutor relies on nonverbal ways like facial expressions, body language and eye contact to identify the psychological state of learners, which signifies the degree of understanding and engagement. Thus, integrating an emotion recognition feature into an intelligent tutoring system, embellish its skills to administer the essential advice, effective tutoring and last but not the least make tutoring session more worthwhile.

1.2 Problem Statement

The creation of domain knowledge capsules is a time-consuming, expensive and herculean task. It requires immense efforts to design and deliver learning content that suits the learner needs and solves learning issues as human tutor resolves in a face-to-face learning environment. The designing of knowledge capsules becomes more time-consuming when the domain knowledge is not well-documented. Thus, gathering such type of knowledge from domain experts is a major challenge. Further, conversion into tutor-able form is another major bottleneck.

Until now, existing ITS has focused mainly on offering learning material based on learner's learning inclination (Weber, (2001)[20]; Gerdes (2017) [21]). Nevertheless, a limited amount of attention has been given to curriculum sequencing, i.e. designing the exclusive learning path for the learner. Thus, incorporating adaptation and personalization features are major challenges for a learning system due to individual diversities and changing learner requirements (Lo, Chan 2012) [22]. Therefore, a Custom-Tailored Curriculum Sequencing module is introduced in 'SeisTutor' aiming to bring personalization and adaptation features.

Hence, the problem statement is:

"A Learner-centric Knowledge-based tutoring engine with Dynamic Profiling and Pedagogical Recommendation for Seismic Data Interpretation."

1.3 Need and Motivation

With the advancement of internet technology, it has been observed that there is a rapid growth in distance learning modality through the web. This mode of learning is better known as the e-learning system. These systems present low intelligence because they offer a pre-identified learning frame to their learners. The advantage of these systems is to offer to learn anytime and anyplace without putting emphasis on a learner's needs, competency level, and previous knowledge. Every learner has different grasping levels, previous knowledge and preferred mode of learning and hence the learning process of one individual may significantly vary from other individuals.

From the literature, it has been inferred that, if a learner's previous knowledge and his/her preferences have been prior-identified, then learning can be recommended in such a manner that enhances the learner's learn-ability. Therefore. The overall effectiveness of ITSs is grounded on the identification and recommendation of an exclusive learning path, i.e. Tutoring Strategy (Custom-Tailored learning path), an amalgamation of Learning Style, Learning Profile, and previous knowledge by Pedagogy Model. Thus, the recommendation and alignment of learning material as per learner's previous knowledge, competency level and imbibing level of the learner is one of the novel aspects of ITS. Embedding this cognitive intelligence in ITS is one of the major challenges in ITS.

There are various challenges in knowledge-based ITS:

i Pre-deciding the rules for creating Tutoring Strategy

ii Often sometimes experts have to create many rules (considering all possible cases) to address a particular scenario. (for example: suppose there is a question in which the learner has to find out the number of the possible paths from source to destination, then experts have to create many rules (based on all possible cases) for solving the same problem).

The creation of the knowledge base is highly expensive and laborious task. The effort of creating knowledge units (capsules) is multiplied when the knowledge is highly individualistic. This kind of knowledge is gradually gained through experiences and hence present in tacit form. Explicating tacit knowledge from experts act as a significant bottleneck because experts deduce some conclusions in his/her mind, lacking proper justification. Therefore, gathering experiential knowledge and their representation is another major challenge.

1.4 Research Gaps

ITS has various research gaps, out of these few of them, are taken into the scope of the current work to address. Following are the few gaps that have been proposed to be incorporated in present ITS:

i Issues in the acquisition of tacit knowledge (Seismic Data Interpretation) from the experts.

ii Challenges of explication of tacit knowledge.

iii Non-availability of knowledge repository for tacit knowledge of Seismic Data Interpretation domain.

iv Lack of generation of exclusive Tutoring Strategy (Learner-Centric).

v Lack of sequencing of learning material as per learner preference and previous knowledge.

vi Lack of adaptivity through pedagogical recommendation.

1.5 Research Questions

Development of ITS presents several research questions. Following are the few research questions drawn from the literature that have been addressed by the proposed ITS:

i. *What are the steps involved to gather experiential knowledge from domain experts?*

ii. *How to represent experiential knowledge?*

iii. *Due to the lack of evidence to justify the fact, how this kind of knowledge is to be converted into tutor-able form?*

iv. *On what criteria, learning material is aligned as per learner preference?*

v. *How to generate a course coverage plan, which is exclusively designed for the learner?*

vi. *How a system can identify the learner preferences, exclusive course coverage plan and give a custom-tailored pedagogical recommendation for adaptivity?*

1.6 Scope of Research

This research work is primarily focused on **Pedagogy Model** and **Domain Model** (see Figure 1.4) of the ITS. Therefore the current scope of the work is focused on the design and development of a Learner-centric Knowledge-Based Tutoring engine that gives exclusive Tutoring Strategy as a pedagogical recommendation to tutor the domain knowledge of SDI.

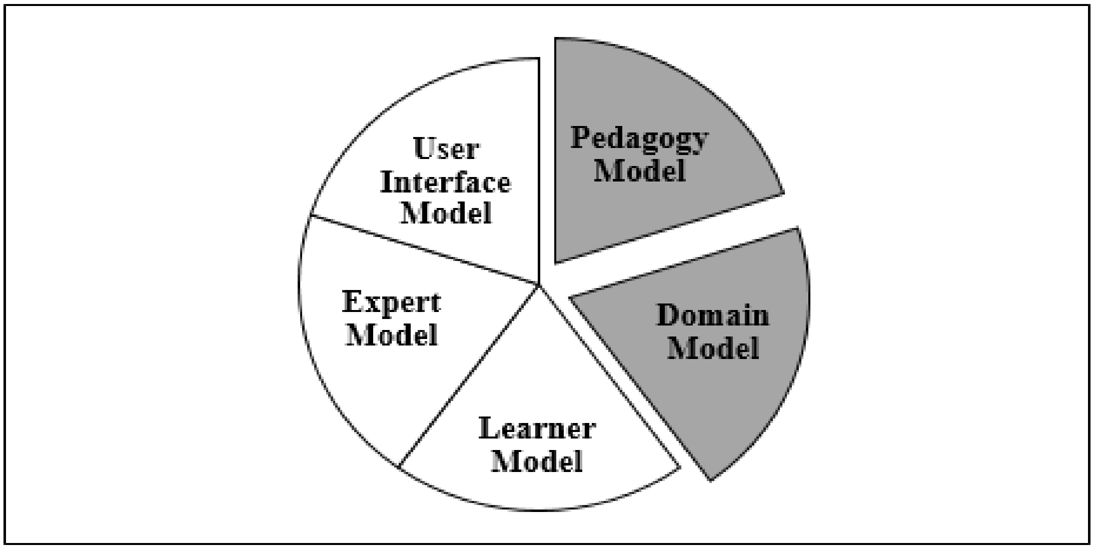


Figure 1-4 Working Model

1.7 Objectives

A Learner-centric Knowledge-based tutoring engine with Dynamic Profiling and Pedagogical Recommendation for Seismic Data Interpretation.

The sub-objectives are:

- To design and develop an adaptive knowledge-based tutoring engine.
- Development of dynamic profile, exclusive Tutoring Strategy and pedagogical recommendation for the learner.
- Content development and delivery through a learner-centric learning path based on Tutoring Strategy.

1.8 Contribution of Research

The proposed ITS is christened as *SeisTutor* because the domain knowledge in this ITS is "Seismic Data Interpretation." As mentioned in Section 1.7.1, this domain is highly tacit because of the lack of thumb rules and predominantly dependent on interpretive powers, capabilities, and experience of human experts, the seismologists. This knowledge is gained over a substantial period. Thus, novice seismologist has to undergo a lengthy training period or wait to gain enough field experience naturally with passing time.

SeisTutor is an attempt to address this problem. Necessary seismic interpretation skills with the fundamentals of this field have been gathered to form the subject matter. This knowledge, initially in tacit form, has been transformed into explicit form and further to tutor-able form. As each learner may have a different competency level and learning pattern, *SeisTutor* has been developed, to initially interrogate, to adjudge the learner sufficiently, to offer learning through an exclusively designed learning plan, referred to here as 'Tutoring Strategy.' Further, it also assesses the learner as per his or her performance during the tutoring sessions.

While *SeisTutor* does not guarantee complete mastery of the subject matter, it is a modest effort in the direction of making the knowledge on this rare domain available in the tutor-able form and also offered in a learner-centric form (as per individual learner preferences).

The research work in this thesis has made some significant contributions to the field of intelligent tutoring systems, listed as below.

1.8.1 Development of Adaptive Knowledge Base

One contribution of this work is to develop personalized learning material through the implementation of the adaptive Domain Model by considering learner characteristics and performance into consideration.

SeisTutor holds knowledge capsules on the subject domain *"Seismic Data Interpretation*. The primary task is to gather experiential knowledge (tacit) from the experts and convert it into an explicit form using existing tacit knowledge acquisition techniques. Further, one step forward, this explicit knowledge is designed and aligned into a total of twelve different Pedagogy Styles (a combination of learner's profile and learning style). Thus, *SeisTutor* is having a total of twelve knowledge capsules, which is capable enough to address the learners differently. Hence, *SeisTutor* is built with an adaptive knowledge base, that offers personalized learning material based on Learner Profile and Learning Style.

Presented below is an example, describing recommendation of the personalized learning material, by determining pedagogical styles of learners.

Assuming learner's Learning Style test score is : Imagistic =9, Acoustic =3, Intuitive = 5, Active = 8 and the learner's level score is Beginner = 9, Intermediate = 4, Expert = 7. Considering a combination of both the test scores in increasing order, a list of pedagogical styles are listed and maintained by SeisTutor as a priority queue. For example, in this Pre-Test case, following pedagogical styles have been listed Priority-wise: {(Imagistic-Beginner, 1), (Active-Beginner, 2), (Intuitive-Beginner, 3) and (Acoustic-Beginner, 4)}. Similarly, beyond the highest scores of 'Imagistic' and 'Beginner', further combinations of the next highest scores of Learning Styles and

Levels are listed and maintained. In this Pre-Test case, the learner appears to be more of a 'Beginner' in terms of level and having a higher preference for 'Imagistic' Learning Style, than any other styles, hence 'Beginner + Imagistic' Pedagogy Styles is identified, to be executed for him/ her.

1.8.2 Learner-Centric Curriculum Recommendation

The aim of this part of the contribution is to develop a personalized learning path or learner-centric curriculum through the implementation of the adaptive Domain and Pedagogy Model by considering learner characteristics and performance. To bring an adaptive and personalized learning path Pedagogy Model plays a vital role in ITS. With the collaboration of both the models, proposed ITS offers personalized learning paths. Learner previous knowledge is examined to provide personalized tutoring. By implementation of Bug Model, the Custom-Tailored Curriculum has been determined. The Bug Model is used to identify the learner's bugs (misconceptions) during the Pre-Test. In literature, this model is used to recommend the post-test remedial solution. In this research, a similar phenomenon of the Bug model is used. However, in the current context, it is used to identify the learner's previous knowledge and errors, and based on that, recommend an exclusive curriculum plan at the beginning of the learning session.

1.8.3. Personalized Tutoring Strategy

To provide a personalized learning environment for the learner, proposed ITS incorporates intelligence techniques, which have been detailed in upcoming sections. These intelligence techniques take various learner characteristics (Learner Level and Learning Style) and educational parameters (previous learner knowledge, the facial expression during learning, learner performances) into consideration, to provide a personalized learning path (learner-centric curriculum) as an exclusive 'Tutoring Strategy' to the learner.

1.8.4. Identification of Learner Understand-ability

To access the overall learner's understanding of the concept a performance analyzer test has been built, where the learners are asked to summarize and write their understanding in the form of text. Based on this summary, the 'Degree of Understanding' score is computed. Performance assessment done periodically is also utilized for quantifying the learning gains of the learner through the ongoing learning journey. This is the non-psychological assessment of learners.

1.8.5. Identification of Learner Emotional State

To recognize a learner's emotional state, a ‘CNN based Emotion Recognition Module’ is developed that uses Machine Learning. This module helps to identify the learner's emotions during ongoing learning. This is a psychological assessment of learners.

From the literature study (Section 2), it is observed that learner emotions help to determine not only learner’s inner cognitive state, but also help to assess the effectiveness of the tutoring system (learning material and tutoring mechanism).

1.9 Intelligence in SeisTutor

1.9.1 Learner-Centric Curriculum Recommendation

Understanding the learner's previous knowledge and recommending an exclusive learning path is considered as Constraints Satisfaction Problem because it involves the determination of the level of knowledge on the course, realignment, and sequencing of learning material as customized curriculum. Constraints are the rules or policies designed to fulfill the objectives. There are two types of constraints, i.e. hard and soft constraints. Violation of constraints is not allowed in hard constraints, conversely, most optimal solution is considered in soft constraints. In this work, hard constraints are imposed using Bug Model while soft constraints are imposed for determining the personalized curriculum. The Bug Model is used to identify the learner's bugs (misconceptions) during the Pre-Test and based on the bugs personalized curriculum is determined.

1.9.2 Identification of Learner Emotional State

The CNN based emotion recognition module is implemented using Machine Learning Techniques of artificial intelligence, i.e. Convolution Neural Network (CNN). Literature on Facial Expression Recognition (FER) reveals that a Convolution Neural Network is best for real-time face pose, face location, and facial scale deviations in terms of accuracy (training and testing). Therefore, for emotion recognition, nine layers based CNN module is developed.

1.9.3 Degree of Understanding

The degree of understanding module is implemented using semantic analysis (Natural Language Processing), i.e. word-based summary analysis. This module requests the learner to write their understanding. Further, their responses are analyzed to obtain scores and compute the degree of understandability (learner attainment level).

1.10 Structure of the Thesis

This thesis has been organized into eight chapters.

Chapter 2: describes the background details and literature review on Intelligent Tutoring Systems/ e-learning systems, the importance of tacit knowledge, how tacit knowledge explication helps in organizational growth, learning path sequencing in e-learning and ITS, followed by the significance of capturing psychological parameters during tutoring.

Chapter 3 describes the design of the Domain Model, followed by a detailed discussion covering the development of an adaptive knowledge base and a multilevel hierarchical representation of knowledge.

Chapter 4 describes the conceptual flow of SeisTutor and adaptation modules incorporated in the Pedagogy Model, followed by the design of the Custom-Tailored Curriculum Sequencing model, Tutoring Strategy Recommendation model, and Learner Performance Analyzer Module (psychological and non-psychological).

Chapter 5 describes the implementation aspects of the proposed adaptive model in *SeisTutor*. In this chapter, the execution of *SeisTutor* with illustrations is presented.

Chapter 6 details the evaluation of learner performance through developed ITS- *SeisTutor*. In this chapter, the statistical methods and their applications on the learner performance is presented.

Chapter 7 details the obtained results under the evaluation of learner performance through developed ITS- *SeisTutor*. The results of the pre-tutoring tests and the post-tutoring tests in terms of learning gain are discussed. The Kirkpatrick's four-phase evaluation is used to determine the effectiveness of *SeisTutor*. The effectiveness of the proposed system, *SeisTuto*r evaluated through learner feedback questionnaire and the learner's emotional state is presented. The learner observations on the adaptivity of the knowledge base and exclusive curriculum features are evaluated through comparative study with the existing ITS.

Chapter 8 concludes with a summary of the research contribution, conclusion, and future scope.

Chapter 2 Literature Review

This chapter presents findings in the field of Intelligent Tutoring Systems (ITS) and the progression of ITS in terms of incorporation of Artificial Intelligence (AI) and Machine Learning (ML) techniques for intelligence in teaching pursuits, the subject matter tutored, the domain knowledge issues covering experiential domain and its acquisition, exclusive learning path sequencing and emotion recognition of learners during ongoing tutoring.

2.1 Background

In this section, a comprehensive coverage of the development of ITS from traditional Computer-Aided-Instruction (CAI) to an Artificial Intelligence techniques embedded tutoring systems is discussed.

Computer Aided Instruction (CAI) systems store the learning material, which is further used by learner in different ways (representation) [Lawler, 1987] [23]. These systems have several limitations. These systems mainly focused on quantitative education (teacher-centric) rather than qualitative nature (learner-centric) of education. Highly primitive tutoring strategy is adopted by the CAI systems which leads to less interaction between CAI tutor and the learner. Further advancement led to the origin of the field of Intelligent Computer Aided Instruction (ICAI) or Intelligent Tutoring System (ITS) [1].

The goal of ITS is to overcome the shortcomings of CAI system. ITS is also known as cognitive tutor because it offers learning material that best suits the learning preference of the learner. These systems offer adaptive tutoring by utilizing Artificial Intelligence (AI) techniques [Kearsley,2005] [24]. The emergence of ITS makes teaching more effective because it takes care of the specific needs of the learners, guides and monitors the learning progress of the learner and provides necessary feedbacks to the learner during tutoring session.

The first intelligent tutoring system (ITS) was modernized in the year 1950 in the form of CAI (B.F. Skinner, 1950) [25]. McDonald, Woolf developed intelligence embedded Computer-Aided-Instruction, that deliver learning material by establishing effective interaction with the learner. Thus, these systems emulate cognitive intelligence of human only to a small extent, i.e., provide necessary guidance based on learner's action. However, all the aspects of the learner model are not handled appropriately by this system. Additionally, learning material becomes too large to embed directly into the programming.

ITS developed by (Uhr 1969) [26] creates questions on vocabulary and arithmetic, but unable to adapt and model learner needs. In advancement to this, several adaptive systems developed by the researchers (Sleeman & Brown, 1982) [27] (Woods and Hartley,1971) [28] (Suppes, 1967) [29].

However, the Learner Model and Pedagogy Model were not adequately explored. The learner demographic information, performances, action activities not properly warehoused. These were the pioneer ITS. Another system subsequently developed known as "drill and test." These systems undertake learner's performance and response as a pivotal criterion to determine and recommend the next tests as well as the next upcoming learning material. However, these systems are unable to provide the necessary guidance in the form of feedback, which further led to a research gap in the development of a new era learning system.

Advancement in the learning systems led to significant modifications in the architecture of ITS. Further improvements in Pedagogy Model led to adapting the learning material to learner competency. Thus the focus of incorporating AI techniques shifted to fine-tune pedagogical recommendation and learner feedback.

An intelligent tutoring system developed by the Andes comprises Physics as the knowledge domain (Gertner and VanLehn, 2000 [13]; Conati et al., 2002)[5]. For decision making, they utilize a Bayesian network. Physics is a well-documented subject domain. The Andes incorporates an intelligent feature of determining performance parameters, predicting learner's subsequent actions and identification and recommendation of a suitable strategy. In the Andes, the physics problem is segregated into sub-problems and further used to build a Bayesian network. Further, this network helps to determine the best feasible learning path.

IntermediActor utilizes fuzzy techniques to determine previous knowledge of the learner and used concepts of data structure (graph) to sequence the learning material.

SQLTutor uses the Artificial Neural Network to determine what learning material should be presented next. Therefore, learning psychology during learning sessions and learner's responses to a task is taken into consideration (Mitrovic, 2002 [8]; Mitrovic, 2003 [15]).

C++ Tutor is an ITS developed by Mooney. With this tutoring system, questions were delivered in the form of feature vectors. Here the learner's responsibility is to identify the vectors and label them. They use the NEITHER algorithm to improve the rule base which further helps to deduce the learner perceptions based on the solution's provided by the learner. This whole process is christened as "THEORY REVISION". At the end of this procedure, the system demonstrates the misconceptions of learners.

CIRCSIM Tutor is a dialogue-based ITS, developed by Evens. The Domain Model comprises of physiology as a subject domain. In this, ITS, learner model is further segregated into four modules: tutoring history, learner history (response), performance, and learner solution.

(Chakaraborty, 2010) [30] presented a review on existing ITS and deduced following research gaps: absence of Custom-Tailored course coverage plan, Creation of a customized knowledge pool, Customized representation of learning material, and Customized characterization of the learner.

VisMod is an ITS developed by Zapata-Rivera (Zapata-Rivera and Greer, 2004 [6]). This system has three-level hierarchical architecture and claims to deliver learning material on a variety of subject domains to the learner.

2.2 Domain Model

The Domain Model is the base for providing the adaptability in the ITS/E-learning systems. For the current scope of work, 'Seismic Data Interpretation" is considered as a subject domain. Seismic Data Interpretation" (SDI) subject is observed to be having a high degree of tacit-ness due to the absence of rules for seismic interpretation. Therefore, this knowledge is known as experiential knowledge which is gained through experience. For the construction of an adaptive Domain Model, acquisition of tacit knowledge followed by the realignment of the acquired knowledge as per Learner Profile and Learning Style has been performed.

2.2.1 Experiential (Tacit) Domain Knowledge

This section covers knowledge, its forms as in the context of making it available for tutoring through tutoring system.

Knowledge is considered an essential asset. Knowledge management produces and disseminates knowledge and information, offers effective utilization of knowledge to have a strategical enrichment for the organization (Nawaz et al., 2014) [31]. As per Liebowitz and Beckman, knowledge management, inherently maximizes organizational knowledge related effectiveness (motivate innovation, superior performance, build new capabilities) (Lytras, Pouloudi and Poulymenakou, 2002) [32]. As per (Wu and Chen, 2014) [33], Knowledge

Management is considered as the operational strategy for an organization because it facilitates them to create new innovative business processes to enhance their performance.

Knowledge is classified into two categories, tacit and explicit knowledge. A new innovative idea is born when there is a collaboration between explicit and tacit knowledge. Existing literature classifies knowledge as theoretical or practical, internal or external, foreground and background. The categorizing of explicit and tacit is the most common aspect of knowledge (Nonaka, 1994, Pathirage, 2007) [34] [35]. Tacit knowledge is an alternative form of experiential knowledge. Experiential knowledge is the factual information gained from own experience with circumstances compared with the knowledge gained through reasoning.

For organizational growth, tacit knowledge plays a vital role that comprises experiences, movement skills, implicit thumb rules, and intuition. There is a considerable difference between tacit knowledge and explicit knowledge. Explicit knowledge is well-documented knowledge (O'Dell and Grayson, 1998) [36], while tacit knowledge is presented in the heads of the individuals exists in the form of perspective, personal beliefs, and values (Baumard, 2002, Borges, 2013) [37] [38].

Some researchers claim that knowledge falls neither purely in explicit nor purely in tacit. However, knowledge lies somewhere in the middle. Nonaka (1998) [39] also emphasizes the importance of associations between explicit and tacit knowledge and also states that tacit and explicit knowledge is not a separate entity; instead, they are a complement to each other.

Polanyi defines tacit knowledge, as that cannot express verbally; it presents in the human brain. (Polanyi, 1966) [40] precisely put a phrase on tacit knowledge, "we used to express less than we know." Tacit knowledge is entirely different from explicit knowledge as it is not easy to transfer and code by conventional mechanisms. Polanyi (1998) [41] states that "knowing how" and "knowing what." "Knowing how" indicates that something attainable in action and "Knowing what" indicates that something lucid. Tacit knowledge can easily understand through the concept of proximal and distal. Distal addresses the action, whereas the proximal addresses the particular action in depth. For example: when cooking food. Proximal knowing is how to cook food (concentrate on the ingredients) while distal knowing is the overall knowledge of cooking food (Berente, 2007) [42]. Tacit knowledge includes a range of sensory and conceptual information. An image is created in a sense to make a sense (Hodgkin, 1991) [43]. There are numerous definitions of tacit knowledge. However, this definition is used to define how tacit knowledge is different from explicit knowledge (Linde, 2001) [44]. Management literature admits that tacit knowledge is essential, difficult to imitate, unique, and gained through experiences (Chen and Mohamed, 2010; Nonaka and Takeuchi, 2004) [45] [46].

2.2.2 Experiential Knowledge Acquisition Approaches

This section covers the various ways through which the experiential knowledge is explicated and made available for use. The utility and challenges are discussed.

Experiential knowledge acquisition is considered to be an essential task for organizational welfare. Thus, the following are the techniques used to acquire tacit knowledge:

2.2.2.1 Cognitive Map

A cognitive map is used to portray the belief of the subjects (Eden et al.,1981) [47]. Eden worked to comprehend and deduce the subject's perceptions and tries to discover how the subjects perceive and illustrate the surrounding things (Eden, 1990, p. 37) [48]. The subject's tacit knowledge is represented in the form of a map. This map is further explored to represent the subject's opinions on a particular problem. There are various types of cognitive maps (Huff, 1990) [49]. The causal map is one of the types of cognitive maps. The Causal map is also a way of gathering and representing tacit or experiential knowledge with the help of graphical notation (nodes indicates the opinion while edges indicate the linkage between the concepts).

2.2.2.2 Causal Map

A causal map is the most reliable technique for explicating experiential knowledge because its prime focus is on activities (Huff, 1990)[49] and also helps deduce the supporting evidence of belief. As illustrated earlier that it is a graphical representation of experiential knowledge, where nodes indicate the activity and edges indicate the relation or working steps (causalities). Perceiving and emulating specific experiential actions over a period of time, the subject, deduce some rules for the beliefs that are consistent for a particular task.

Experiential knowledge is gathered in a causal map by gathering the subject's experiences. During map constructions, subjects are requested to illustrate the scenario, constraints, obstacles, actions, behavior, and the results. This probing helps to reveal the hidden, and unarticulated skills. Thus, this indicates the transitions of knowledge from tacit to explicit.

2.2.2.3 Self Q

Self Q is a self-interviewing practice, helps to deduce the subject's thought process. In this technique, subjects interrogate themselves. The subjects are the sole author on his/her knowledge, thus based on his/her knowledge, he/she interrogate a specific frame of questions (includes a parameter, situation) to explicit their tacit knowledge (Bougon, 1983) [50]. This technique is profound to be a promising technique because the person knows herself/himself better than others.

2.2.2.4 Semi-Structured Interview

In this knowledge extraction technique, the aim is predefined. The interviewer explores to know the complete story (factor, situation, steps, and constraints) of a subject's experience. According to (Ambrosini, 2001) [51] narrating experience is considered to be adequate to explicit their implicit knowledge; thus, there is a need to encourage the subjects to share knowledge. From the research, it has been observed that narrating stories discloses more hidden information than regular sharing of knowledge (Rabionet, 2001)[52].

2.3 Pedagogy Model

Pedagogy Model is the brain of an ITS/e-learning systems, responsible for providing adaptability and personalization features.

2.3.1 Path Sequencing of Learning Material in Learning Systems

This section illustrates the preliminary research work on path sequencing of learning material in an intelligent tutoring system/e-learning system/learning management system.

As discussed in Chapter 1, an ITS is a rule based system, and the programmer defines all possible rules that address specific circumstances. These rules indicate that it follows a predefined curriculum and offers remedial actions based on learner activity like human tutors do [53][25][54].

A depth-first traversal algorithm was used for curriculum sequencing in Knowledge-based Systems [55]

ITS developed by Chen(2011) [56] offers a personalized learning environment by offering learning material to the learner based on previous knowledge about the course. To adjudge previous learner knowledge Pre-Test plays an important role. The pathfinder technique has been used to determine previous knowledge of the learner.

The concept map is another technique that has been used to depict the relationship between the topics and associated subtopics in the form of nodes and edges, where nodes indicate the topics and edges indicate the relation. Nonav and Canas suggest this notion of concept map. They infer this notion from the theory of Ausubel [57].

ITS developed by (Haoran Xie, 2017) [58] proposed a solution for determining the learning path for a group of learners. They utilized a profile based framework for determining appropriate learning path.

Further advancement in this field uses a data mining technique to mine the meaningful learning path for the learner. This kind of system tracks learner activity during learning and recommends the most suitable learning path. ITS developed by (Tung-Chen Hsieh, 2010) [59] incorporated two methodologies, one is determining the learning path, and the other is recommending the learning path. Initially, the system utilizes the apriori algorithm to generate an initial course coverage plan; further, they used formal concept analysis to determine the association between the concepts and then adjudge preferable course coverage plan.

Another [60] proposal uses, a fuzzy rule base technique utilized to determine the association between the list of materials and learner requirements based on web navigation. In recent development in technologies some concept of ontologies, genetic-based algorithm and artificial neural network are used to recommend a suitable course coverage plan [61] [62].

ITS developed by (Chen, 2008) utilizes the nature-inspired algorithm to adjudge the Custom-Tailored learning path. They used two critical parameters for fitness function; one is difficulty level and other associations between the course concepts. Another research work on e-learning system makes use of the nature-inspired algorithm for determining optimal course coverage plans based on the incorrect response on the Pre-Test (Chen, 2008; Agbonifo and Obolo, 2018)[63] [64].

In a recent development, a bio-inspired artificial intelligence, i.e., Ant Colony Optimization (ACO), is utilized for determining the course coverage plan. Initially, the ant-based system [65] utilized the Traveling Salesman Problem (TSP). This mapping helps to determine the optimized learning path. This learning path represented with the help of graphs with weighted edges that indicates ant pheromone (students) i.e., released pheromones along their path.

In [66], the author uses ACO techniques to recommend an adaptive learning path by taking learner's Learning Style into consideration. [67] Utilizes self-organizing techniques to recommend optimal course coverage plans to the learner. Similar practices can be applied through a probabilistic technique in which nodes indicate the pedagogy items and edge indicates the hypertext links (preferred probabilities) and learner act as ants who have to traverse all the nodes [25,53,61,68,69].

ITS developed by Jamon et al. utilizes an “ant-hill” nature-inspired algorithm, based on learner success/failure ratio for validating an item/topics/concepts ant lay pheromone. Thus, pheromone helps to determine the optimized course coverage plan for learners [70]. A style based Ant Colony system (SACS) utilized advance Ant Colony algorithm. They design the user model by determining a suitable course coverage plan for a group of learners using a graph-based path structure [71] [72].

ITS developed by Sengupta et al. experiments with Ant Colony Optimization to attain the personalization feature in the recommendation of the learning path. They utilized frequent graph patterns to determine the correlation between the concepts [73].

ITS developed by Kardan experiments with a two-phase learning path algorithm. In the first phase, they adjudge the knowledge level of learners based on the performance in the Pre-Test. In the second phase, they used a metaheuristic algorithm to determine and recommend a suitable learning path to the learner. [59]

ITS developed by agbonifo et al. experiments with the learner model. Their developed ITS determine the learner’s Learning Style using *“Honey and Mumford”* Learning Style model. To recommend a suitable learning path for learners, they utilize the Neuro-Fuzzy technique. Here researcher did not consider the difficulty level of learning material [74] [75].

2.4 Impact of capturing Emotion in Learning System

ITS’s are a generation of the computer-based software system; the purpose is to improve and support learning in a particular domain. It emulates human intelligence, offers the benefits of personal teaching and also provides personalized and adaptive learning environment. Here an adaptive learning environment indicates the integration of cognitive intelligence into the traditional CAI.

For era, the notion of ITS has been grounded on the principles of constructivism and cognitivism. They are primarily focusing on learner’s cognitive processes. Recently, researchers have switched their attention from learner’s cognitive processes to learner’s emotion enabled cognitive processes. This switching is due to researcher giving more emphasis to the correlation between learning and emotions. The results from previous research show that emotions play an ample role in the learning process as they are equally responsible in affecting learner’s learning and motivation abilities. Previous research studies deduce that the learner perceives negative and positive sentiments throughout the learning process. Thus, it indicates that more emphasize is to be given to learner's emotion enabled cognitive processes in the development process of the learning system.

2.4.1 Emotion Recognition in Learning System

Murthy and Jadon [76] [77] have taken six emotions, i.e., Sad, Happy, Surprise, Disgust, Normal, and Ambiguous into consideration. For emotive recognition, they utilize Eigenfaces. Their main inspiration was to use the dimensionality reduction technique (Principal Component Analysis) for a more extensive set of data. By using this technique, they achieved 83% accuracy. However, they utilize PCA, which makes this technique more expensive because the computation of the covariance matrix is performed at the expense of efficiency mainly when abundant datasets encompassed for training purposes [77].

Lien and colleagues [78] have considered two approaches, i.e., SVD (Singular Value Decomposition) and direct matching. Firstly, they transformed the images into corresponding transitional expression matrices, and then they perform a direct matching operation. These two approaches impose certain drawbacks, i.e., A direct matching operation provides no or little precision for computing correlation coefficients. Therefore, facial image conversion would result in producing asymmetrical output facial images.

In Arumugam [79], for feature extraction, they integrate FLD (Fisher's Linear Discriminant) and SVD (Singular Value Decomposition), and for the classifier, they utilize Radial Basis Function. Mainly they focused on only three types of emotions, i.e., Disgust, Happy, and Anger. The major drawback of this approach is that they achieve low accuracy by utilizing this combination. The computation of naïve SVD is often going beyond the computation speed and power of various machines [80].

The ITSPOKE ITS is a dialogue system [81] that mentors a learner through a long physics qualitative question by describing every aspect of misconception. To identify the learner's emotional state, i.e., positive, neutral, and negative, they utilize sound and prosodic features mined from learner speech. By using this technique, they achieved 80.53% accuracy.

AutoTutor [82] successfully addresses more refined emotional states, i.e., confusion, boredom, frustration, flow, and neutral. They observed emotions from body posture, conversational cues, and facial features. For valid replies from a tutoring system, they utilize some animated pedagogical agent having animated facial expression, sound, and speech.

Woolf [83] has taken five emotions, i.e., self-confidence, frustration, boredom, motivation, and fatigue, into consideration. He utilized different heuristic rules for providing an adequate response (changing voice and gesture, sympathetic response, graphs and hints, text messages) to the learner's cognitive state. He computed the degree of engagement concerning the overall impact on learner's learning and behavior.

Mao and Li [84] [85] proposed an Emotion-Sensitive ITS named "*ALICE".* Alice utilizes an emotion agent that is effectively capable of recognizing the emotions of the learner through text, speech, and facial expression. They consulted human tutors to discuss all possible scenarios and developed rules. Thus 'ALICE' behaves closest to the human tutors through the ongoing tutoring sessions.

Tian [86] proposed a framework based on the intersection of active listening and affective computing. In this framework, emotion recognized by analyzing the textual interaction, such as sentence typed, group discussion, chat rooms and question, and answer. For providing an effective text-based response, they utilize case-based reasoning.

Strain and D'Mello (2011) [87] had done the analytical study on learner's psychological state while performing any task. Systems initially consider negative emotion of learner towards learning session and begin learning session accordingly; and then answer the questions about what they had learned. The results show that the utilization of cognitive reappraisal as an emotion regulation strategy leads to more positive activating emotions and better reading comprehension.

As mentioned earlier, minimal work concerning learner path sequencing is reported so far in ITS — a couple of instances discussed below.

ELM-ART ITS [53] provides a path sequencing and adaptive hypermedia, which enable the learner to navigate through this material. ELM-ART provides navigation support by utilizing two hypermedia techniques, i.e., adaptive annotation (focus on visual artifacts and their representation) and adaptive sorting (determine the similarity between concepts and offer more suitable concepts),

Summary

This chapter explored the work in the field of Intelligent Tutoring System (ITS)/E-learning System/Hypermedia System for several domains. The related work under various components of

ITS architecture: Domain Model, and Pedagogy Model have been discussed. The Domain Model that is a crucial component of the ITS has been explored in detail. With emphasis on the experiential knowledge domain and their acquisition and explications techniques. The Pedagogy Model that is considered as the heart of the ITS has been explored, in detail, emphasizing on learning path sequencing techniques, used to provide adaptivity and personalization in the ITS/e-learning system/ LMS. Towards concluding part of this chapter, importance of emotion recognition in the ITS/e-learning system/ LMS, is discussed.

Chapter 3 Design and Development Methodology of Domain Model

This chapter describes the development of an adaptive domain model for the tacit knowledge domain. The prime consideration has been inclined towards the development of a knowledge base that comprises twelve pedagogy styles that have been designed as per learner preferences (Learning Style and Learning Profile).

3.1 Domain Model

Domain Model is the heart of an Intelligent Tutoring System (ITS) because the domain model contains the expert knowledge, which is gained through experience and makes available for the novice learner when requested. This model is highly focused on the "What to Teach" issue (see Fig. 3.1). Domain model comprises of "what" is to be taught. The learning material forms content of course (SDI). Knowledge Engineer gathers domain knowledge from the domain experts, realigns and sequences the gathered knowledge under the supervision of the subject domain experts. The aim of the domain model is to keep the subject domain and the learning material as content in the course and deliver it to the learner. This model organizes the subject topic, sub-topics, and their association with other topics.

The organizing of knowledge is in a style and level as per the convenience of the learner, to provide better learning gain.

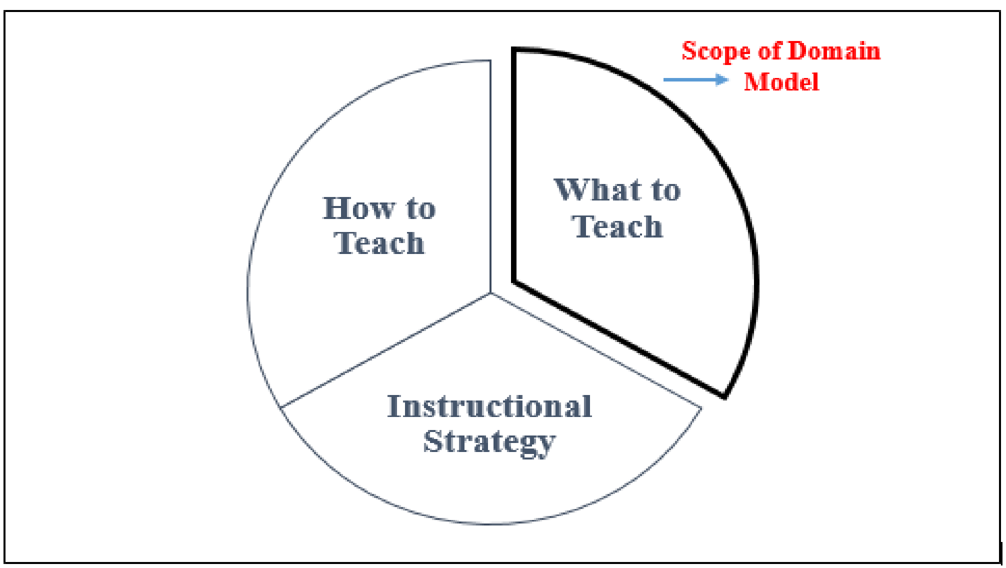


Figure 3-1 Responsibility of Domain Model

For the current scope of work, Seismic Data Interpretation (SDI) is considered as a subject domain. This subject domain is one of the knowledge domains, which is undocumented and highly experiential. Since, the knowledge is gained through experience, without any documented sources available it is qualified as a Tacit Domain of Knowledge.

3.1.1 Seismic Data Interpretation: as a Tacit Domain

Seismic Data Interpretation (SDI) is the sub-field of Geophysics under the field of Petroleum Exploration. The Petroleum Exploration process uses seismic data to understand and delineate the subsurface geology. The final result of the exploration process is further processed and is available for analysis in the form of a SEG-Y map of seismic images. Till date, there are human experts, i.e. Seismologists that analyze SEG - Y maps and discover their understandings. During analysis, experts are trying to understand what kind of subsurface geology exists. This process is termed as interpretation. There are no documented thumb-rules for interpretation. The interpretation knowledge available is 'implicit' within the experts and exists as their mental database. It has been gained by them, over years of experience, and the time spent in the fields. This knowledge is termed as 'Tacit Knowledge'. The lack of documentation, causes the uncertainty to exist, in interpretation. There may be a possibility that the same SEG-Y map may be interpreted differently by different seismologists, because this knowledge, to a great extent, is highly individualistic, and varies from expert to expert.

A novice seismologist joining an organization engaged in Petroleum Exploration processes holds very minimal interpretation powers and needs time and practice to hone satisfactory skills. But this process is time-consuming and expensive intensive. The organizations, incur expenditure on long training cycles, to train them, and let them practice their skills over a period of time, so that they can deliver reasonable interpretation. The major bottleneck is the nature of knowledge, which due to its individualistic and experiential characteristics, incurs long training periods. The focus of this research work is capturing this experiential knowledge, which is present in the tacit/implicit form, converting this knowledge into an explicit form and making it tutor-able. The main reason to explicate this knowledge is to reduce the overall training cycle. Fig. 3.2 describes the distinct features of Tacit and Explicit Knowledge.

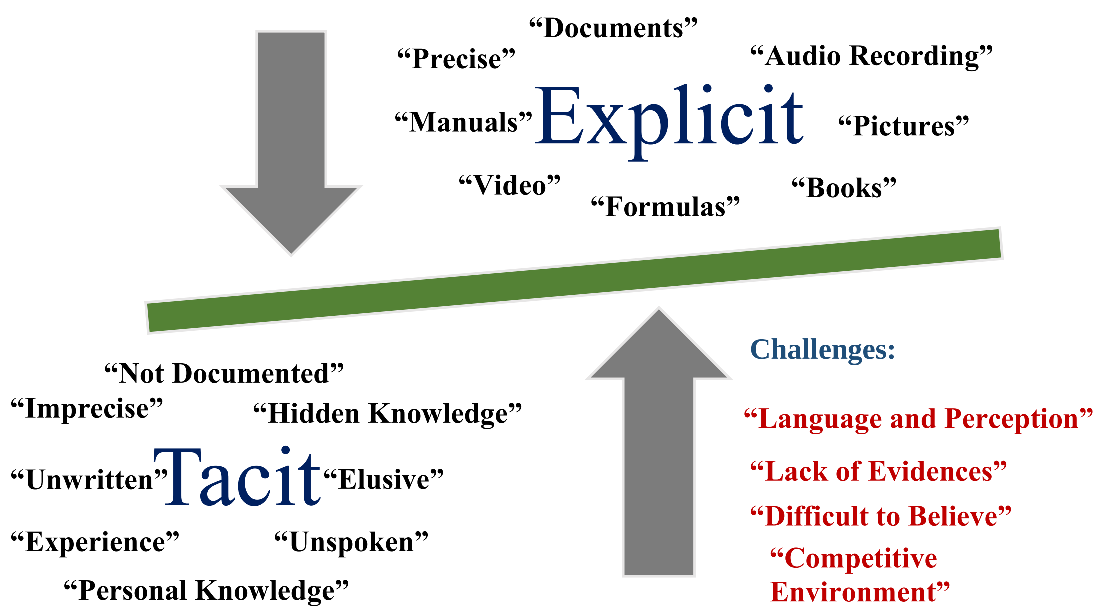


Figure 3-2 Features of Tacit and Explicit Knowledge

3.2 Development of Adaptive Domain Model

This section describes the development of an adaptive domain model or an adaptive knowledge base. The developed domain model comprises of twelve pedagogy styles. Each of the pedagogy styles is distinct to each other. Based on learner preferences most optimal pedagogy styles are chosen. This feature of SeisTutor makes the domain model an adaptive knowledge base, because it enables the SeisTutor to adjudge the learners preferences and provide the learning material accordingly.

For developing the adaptive domain model, the current work has been categorized into two phases (see Fig. 3.3).

The objective of the first phase is to acquire tacit knowledge, characterize it and convert it into an explicit form. In subsequent phases, the explicated knowledge is transformed, into a tutor-able form. For this purpose, the content is shaped as a course with a structured course plan (also referred as, course coverage plan). The content coverage organized into Units and Sub-Units, spread over the coverage time is organized. Various acquisition techniques, i.e. causal map and one-to-one interviews/semi-structured methods, have been used for each of the above steps.

The objective of the second phase is to align the learning material as per the curriculum and make it tutor-able. The packaging of learning material is known as a knowledge capsule. In the present work, the SeisTutor comprises of twelve knowledge capsules. Every knowledge capsule holds same content, but their content representation, usage of rich media techniques and the content elucidation level varies. In several ways, there is variation from capsule to capsule. Therefore, as a result, twelve adaptive knowledge capsules have been developed to offer to the learners, as per the adjudged requirement.

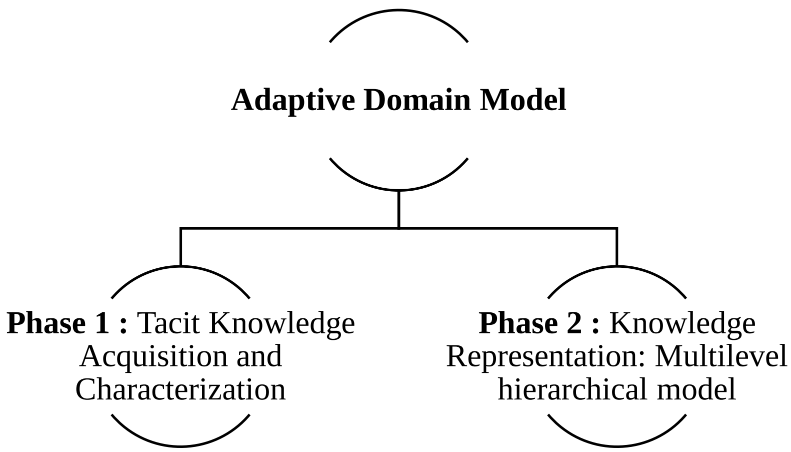


Figure 3-3 Conceptual diagram of the development of the adaptive domain model.

Fig. 3.3 describes the conceptual workflow that has been used to develop an adaptive domain model. Subsequent sections describe the techniques and methodologies used in Phase 1 and Phase 2.

3.2.1 Phase 1: Tacit Knowledge Acquisition and Characterization

This section describes the steps followed to discover and gather tacit knowledge from the experts through causal and semi-structured methods. Fig. 3.4 shows the process involved to solicit tacit knowledge from the expert and then make it tutor-able. In knowledge gathering step, knowledge from basic to advanced levels, on SDI is gathered from experts. In knowledge characterization step, the nature of the knowledge is studied, to clarify and elaborate. The related topics and subtopics are combined, to make a complete unit/package. In knowledge sequencing, the characterized units are re-aligned to form a complete course coverage plan. In validation step, the designed curriculum is verified from the domain experts for their approval. Then, the learning material is organized as individual knowledge capsules as per the validated course coverage plan.

For gathering knowledge on the SDI domain, formal permission was sought from public sector companies who have been involved in seismic data acquisition and interpretation tasks. A total of 09 meetings were held with Deputy General Manager (DGM) and their team. A well-structured questionnaire (causal map construction technique) and one-to-one interviews (semi-structured method) have been used as instruments for domain knowledge collection and conversion.

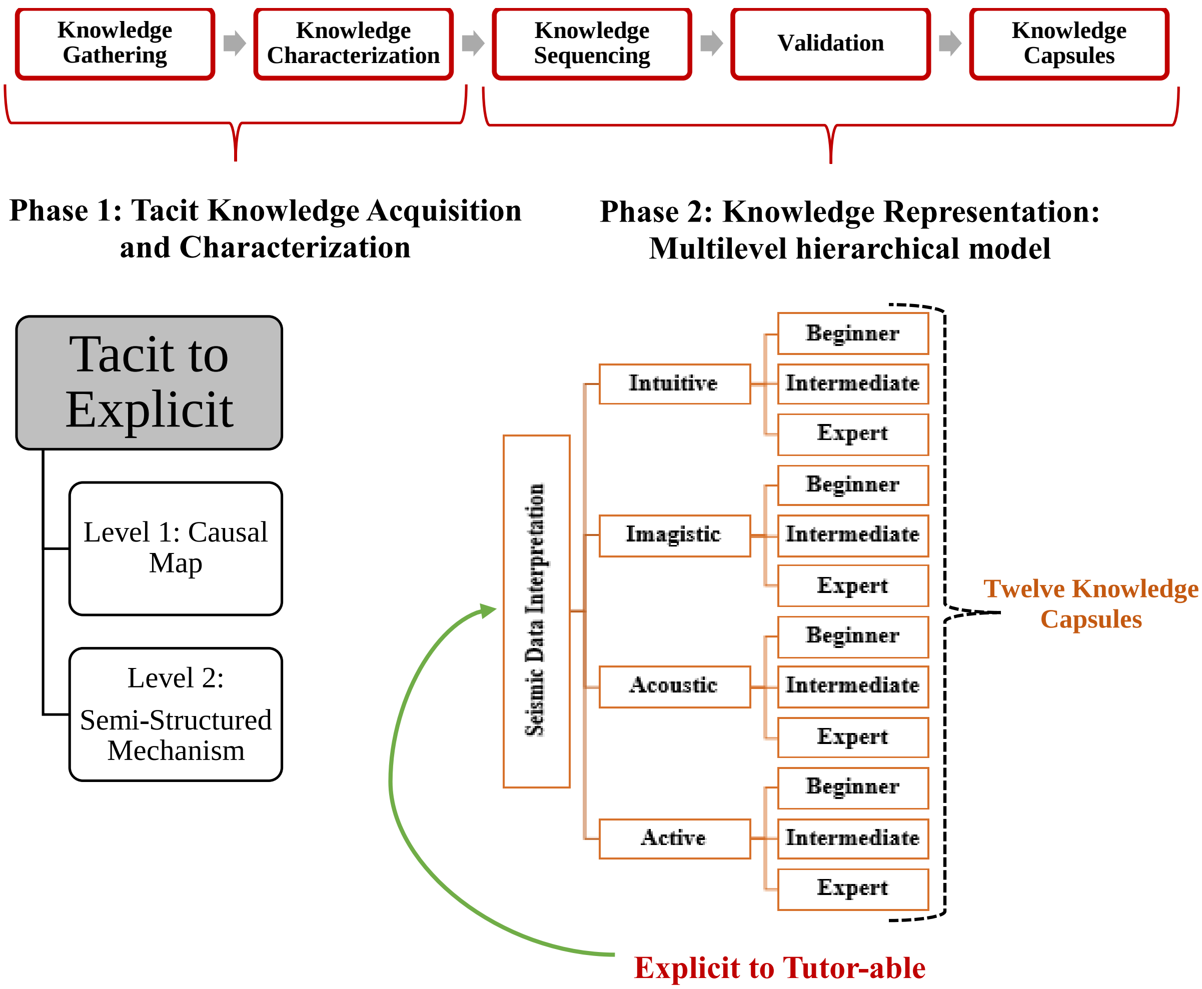


Figure 3-3 Phases involved to solicit tacit knowledge from experts and make it tutor-able

3.2.1.1 Conversion of Tacit to Explicit: Findings

This section describes the experience during gathering tacit knowledge (of seismic data interpretation) and their transformation into an explicit form.

A formal **note-sheet** presenting the general motivation behind the activity is conveyed to the concerned authority. For acquiring tacit knowledge from experts, two independent groups of 2 individual each is created and the task of requesting tacit knowledge from 5 geologists/seismologists was performed. Out of the group of 5 seismologists, 2 were expert profiles (engaged in interpretation skill for more than 12 and 13 years, respectively), 2 were middle-level expert profiles (who had been doing interpreting activities since 3 and 4 years individually), and the last individual was a novice student (recently in-cumbered into the group to learn and to practice hands-on activity on, interpretation skill).

The aim of the formation of a group with varied proficiency of interpretation skill is purposeful, to accumulate all viewpoints and to have enough ways for iterative data gathering and validation. Over a progression of meetings, the process of obtaining and requesting tacit knowledge from geologists/seismologists is performed. Primarily, the causal map is used, in which a series of the questionnaire were made and put forward in front of domain experts by both the groups and accumulate sufficient information which further helps in the construction of the causal map. The first group did their scrutinizing, probing, and causal map development activity. In the causal map, nodes indicate the questions or topics and links indicate the feature of the nodes (normal, important and prediction task). This procedure has taken the time of three weeks by group 1 and the other group took around four-week of time. To accumulate adequate information, questions ranging from, techniques used for seismic data acquisition to analysis to interpretation were developed. Table 3.1 indicates the partial list of questionnaires unfolding the seismic data interpretation process.

3.2.1.2 A partial list of a questionnaire for Causal Map Construction

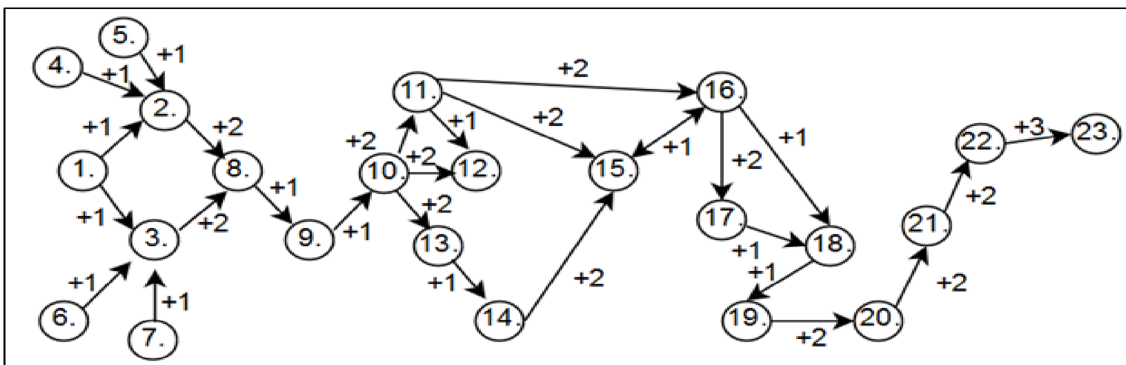
Table 3-1 Partial List of a questionnaire for Causal Map Construction

S.No	Questions
i.	What does the seismic snap indicate?
ii.	Where might you find additional seismic information to affirm the shape and size of the structural trap that you have mapped?
iii.	Kindly explain the scenario where the horizon and faults incorrectly interpreted?
iv.	Illustrates the steps involved in the identification of faults and their types, through velocity correlation?
v.	What are the challenges faced during analysis and interpretation?
vi.	Several stories are revealing that error encounters during an acquisition? Please discuss.

The causal map built by each group is closely examined together to create a reasonably appropriate material representing the conversion of tacit knowledge into explicit knowledge. This piece of work is identified as Level 1.

Terms gathered from the casual map have been listed below:-

1. Seismic Acquisition
2. Onshore
3. Offshore
4. Thumper Truck
5. Geophone
6. Air gun
7. Hydrophone
8. Analog Recording
9. Analog to digital conversion
10. Wiggle Trace
11. CDP Gather
12. Stacking
13. NormalMove-out correction
14. Processed seismic section
15. Common Depth points
16. Floating Datum
17. TWT (Two Way Time)
18. Time versus Depth Conversion
19. Seismic Map
20. Check-line scale and orientation
21. Top-down approach for clarity of understanding
22. Determine primary reflectors and geometrics
23. Prediction of Hydrocarbon amassing



Note +1 :- Normal Task , +2 :- Important Task , +3 :- Prediction Related Task

Figure 3-4 Causal Map for Processes involved in “seismic interpretation domain “

Fig. 3.5 shows the causal map in which the subject theme is ranging from seismic data acquisition and processing to analysis and interpretation. The current scope of this work is to capture the tacit knowledge of seismic data interpretation, whose terms are numbered, from 19 to 23.

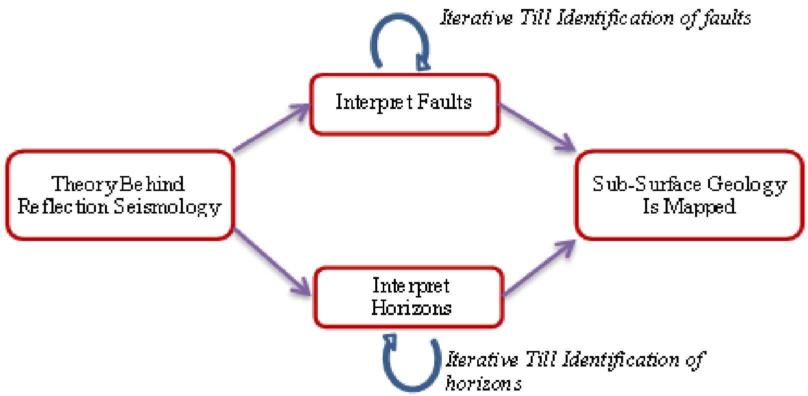


Figure 3-5 Schematic diagram of seismic interpretation task

Fig. 3.6 shows the graphical representation of the interpretation task. For simplicity, faults and horizons are referenced here. Fig. 3.6 reveals that the whole process of interpretation is iterative; with each section repeatedly examines. After accumulating all the translated seismic section subsurface, the topographical map is created.

The built causal map has been further detailed. The exhaustive causal map (step numbered) has been shown in Fig. 3.7. Fig. 3.7 is the continuation of Fig. 3.5 from step number 19, which is numbered from 1 to 9. The depiction of steps recorded beneath:

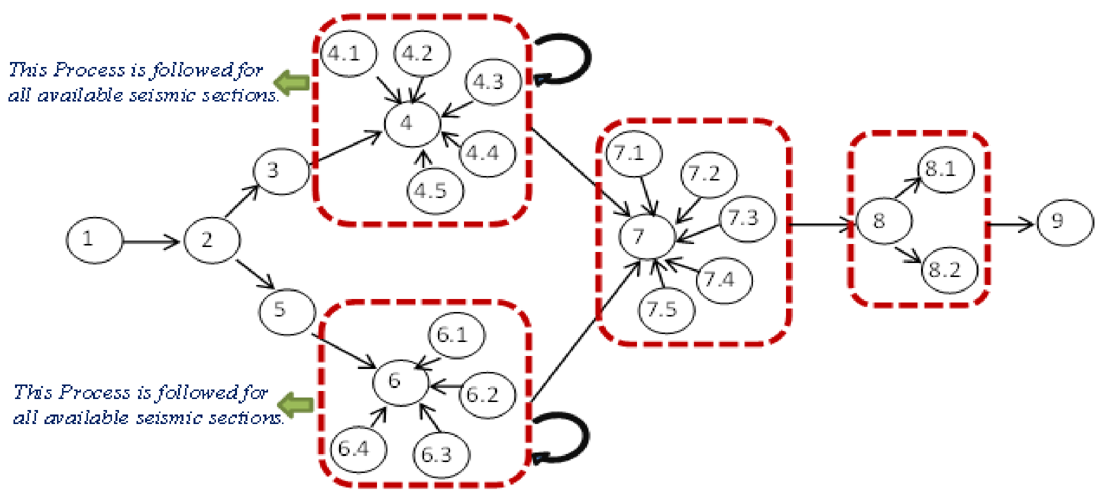


Figure 3-6 Schematic diagram of seismic interpretation task

1. Seismic Map
2. Interpretation initiates
3. Structural Interpretation
4. Structural analysis
5. Stratigraphic Interpretation
6. Stratigraphic analysis

4.1. Faults and folds
4.2 Salt
4.3 Shale Diapers
4.4 Structural Trends
4.5 Structural Features
6.1 Unconformities
6.2 Stratal Packages
6.3 Environments/ Facies/ Lithologies
6.4 Ages

7. Identify Prospect elements

7.1 Source of the geological feature
7.2 Migration
7.3 Reservoir
7.4 Trap
7.5 Seal

8. Assess the Highest Potential Prospects

8.1 How much oil/gas do we except?
8.2 How certain are they?

9. Economical analysis

The semi-structured mechanism is utilized in Level 2 and proceeded with a similar group and same geologist/seismologist groups, as in Level 1. The geologists/seismologists were scrutinized and requested, to share their skills, discoveries, and stories, jot down what worked and what didn't and their portrayals were recorded. The two groups drew out their outcomes from the recorded experience stories and narrations. This activity finished in 5 weeks by the two groups.

The outcomes were cumulated, and a proper record of each topic and subtopics of interest was created. This notion prompted the development of a knowledge capsule. The significant commitment of the present work is to explicate the tacit knowledge in the form of knowledge capsules, enabling its future scope in phase 2.

Fig. 3.8 demonstrates the diagrammatic representation of a semi-structured mechanism, where, the nodes 1, 14, 19, and 23, are shown, that holds the information that should be transformed from implicit to explicit form. These nodes are further probed. Let us consider the probing of node 1, i.e. 1.A, 1.B, 1.C. Suppose if node one is focused on a specific topic, further detailing on that topic are 2.A, 2.B, 2.C, that might be the supporting subtopics to briefly describe the concepts of node one or topic one (where 1,2,3,4 indicates the level of probing while A, B ,C represents the supporting subtopics of particular node). The primary motivation for adopting this mechanism is to get a clear understanding of the topics. Each detailing (probing) attempted has its purpose; the purpose of node 1 is to comprehend the different strategies to accomplish.

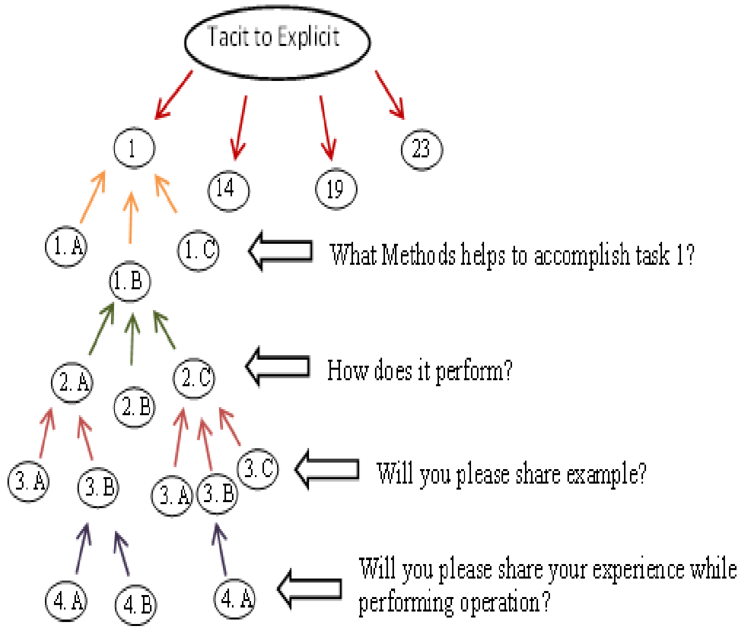


Figure 3-7 Semi-Structured mechanism.

A similar procedure is pursued for the remaining activities (topics/subtopics) 14, 19, till 23. This way, the probing can proceed with further revealed hidden details and eliciting experiences. Figure 3.8 shows the probing of 4 topics up to 4 levels of segregation. The course coverage plan was designed as instructed by the domain experts. Furthermore, the captured domain knowledge has been transformed into knowledge capsules. The development of knowledge capsules puts one level ahead from the explicit representation of the tacit knowledge to tutor-able form. This work is accomplished in phase 2.

3.2.2 Phase 2: Knowledge Representation: Multilevel hierarchical model

This section describes the conversion of explicit SDI domain into a tutor-able form in the form of twelve knowledge capsules. Thus, to accomplish the objective, the course manager and the knowledge repository submodules have been developed that combine to form a knowledge base module. The purpose of the course manager is to align the subject topics, sub-topics based on the association between them. The purpose of the repository is to warehouse the learning material and assessment materials. Learning material and assessment material are described by meta description that aid in maintaining, locating, representation, and reusability of subject knowledge in the knowledge-base.

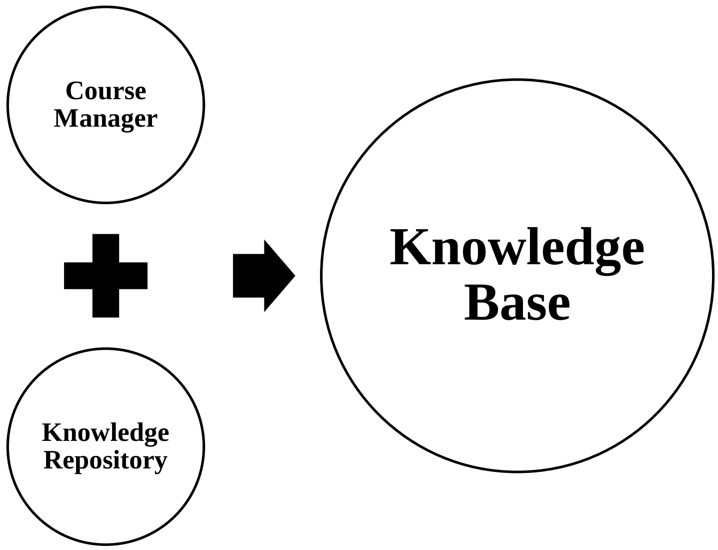


Figure 3-8 Knowledgebase Modules.

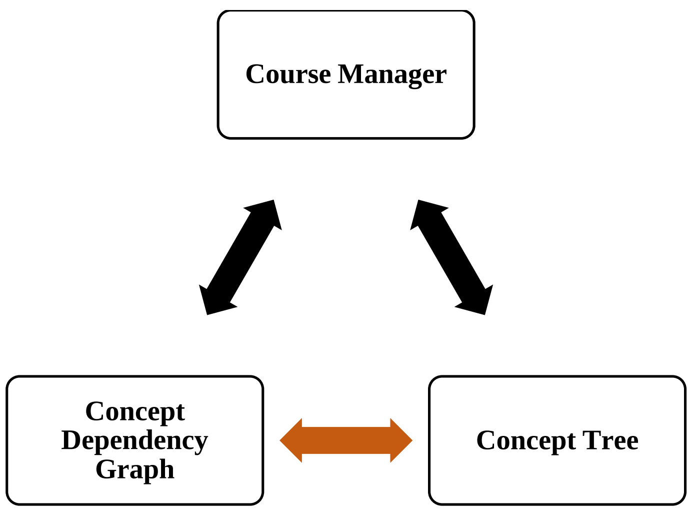


Figure 3-9 Responsibility of Course Manager

3.2.2.1 Course Manager

The course manager is the graphic representation, of course material. It utilizes data structure techniques for its illustration, i.e., Concept Dependency graph and Concept Tree (see Fig 3.11).

3.2.2.1.1 Concept Tree

The concept tree possesses a hierarchical tree-type data structure, where the subject name resides at the root node and topics and sub-topics reside on a leaf node (see Fig. 3.12).

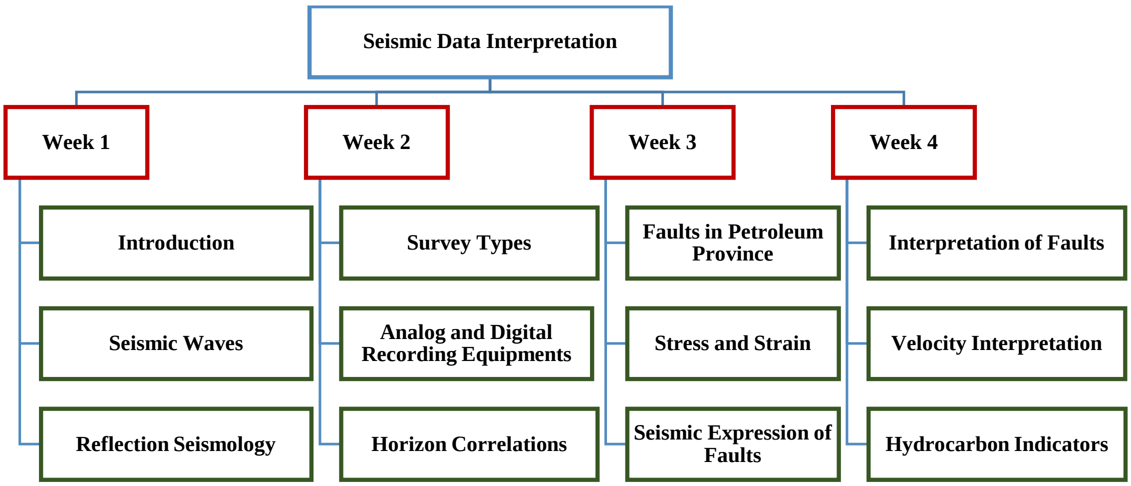


Figure 3-10 Course Tree representation of Subject Domain 'Seismic Data Interpretation.'

3.2.2.1.2 Concept Dependency Graph

The concept dependency graph is the graphical representation of the association between subject topics and sub-topics (see Fig. 3.13). Every domain knowledge warehoused in the knowledge base is the pair representation of concept dependency graph and concept tree which work together and aid in maintaining, locating, representing, and reusability of subject knowledge.

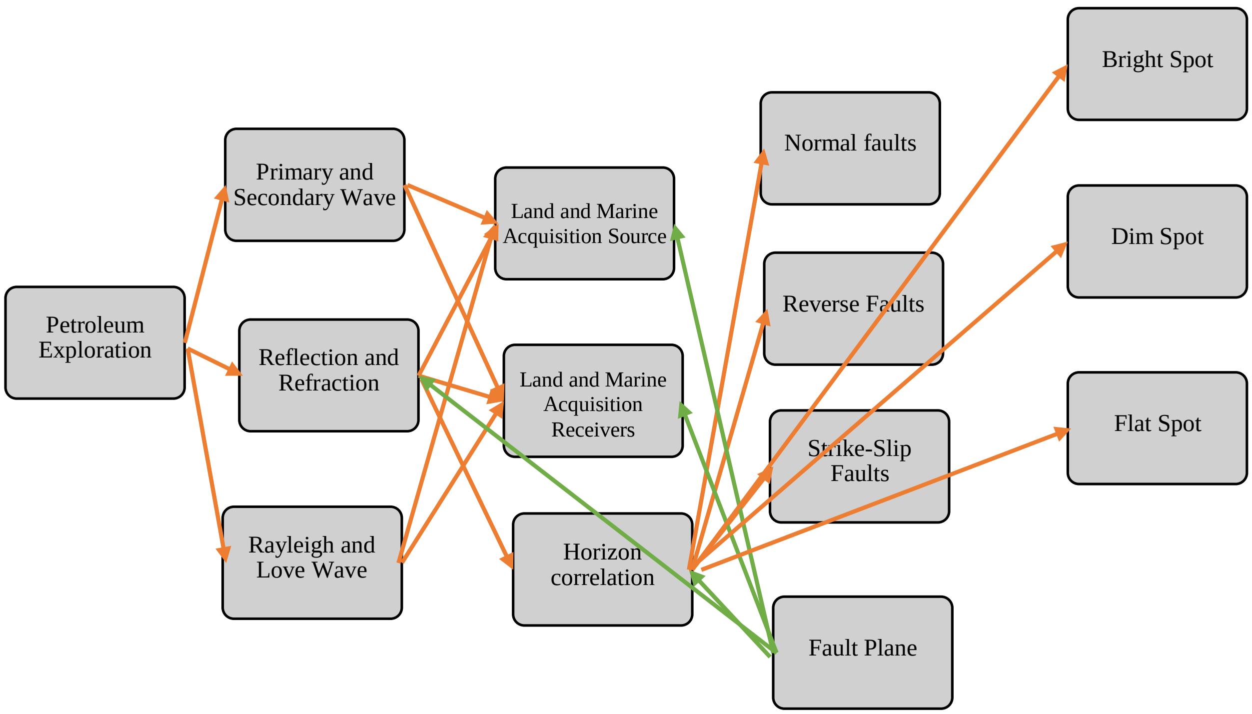


Figure 3-11 Course Dependency Graph representation of Subject Domain 'Seismic Data Interpretation.'

3.2.2.2 Knowledge Repository

Knowledge repository comprises of learning materials and assessment materials. As aforementioned, every learning topic and sub-topics provide meta-description which speeds up the accessing of the learning material from the knowledge pool. The critical issues in the teaching system are overwhelmed by ontologies [88]. The interim web offers a productive, interactive mode of learning by utilizing audio, text, images, pedagogical agents and animation. Which persuades the active interaction between the learner and computer-aided system [19].

Furthermore, this active interaction enriches the persuasive communication, improves problem-solving skills, and over-all learning gain. The ontology-based representation of the subject domain is demonstrated in Figure 3.14. This representation aids in enriching the recommendation of learning materials. The amalgamation of learning material with this kind of representation aids the SeisTutor to pacify the learner preferences (mode of learning, the difficulty level). In the current scope of work, a three-level knowledge base frame is used, that is demonstrated in Fig.3.14.

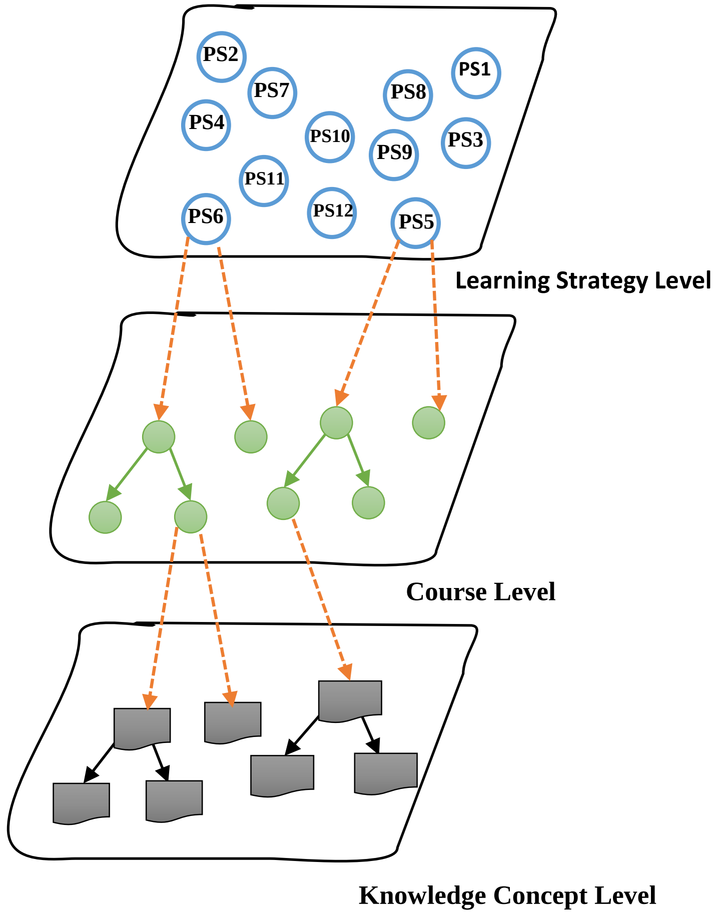


Figure 3-12 Knowledge Base frame

3.2.2.2.1 Learning Strategy Level

SeisTutor comprises of the total twelve pedagogy styles that rely on the productive, interactive multimedia techniques, learning styles (learning preferences), and the learning profile (level of difficulty) (see Fig. 3.15).

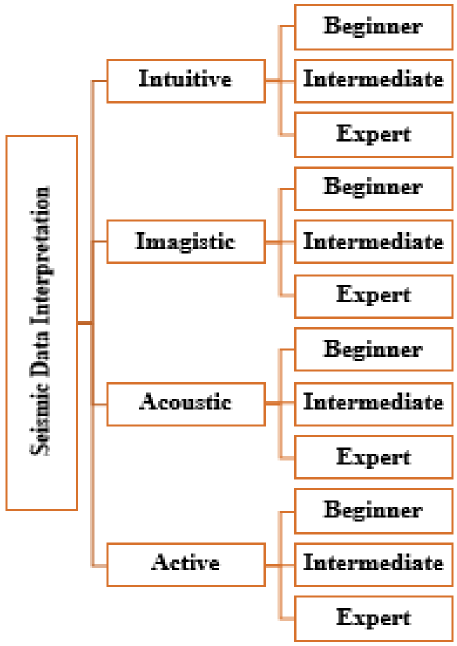


Figure 3-13 Domain Pedagogical structure in SeisTutor (Learning Style and Learner Profile)

3.2.2.2.2 Course Level

The course level is the hierarchical representation of the Week-Wise learning course material.

3.2.2.2.3 Knowledge Concept Level

The subject topics, sub-topics, and their hierarchical representation form a course coverage plan. The course coverage plan also retains the association among the topics, sub-topics (part-of, prerequisite).

Henceforth, domain model in SeisTutor gear with the richness of multimedia amalgamated learning materials. SeisTutor retrieves a portion of learning material from the knowledge base depending upon the learner's profile and learning style. Furthermore, the learning content is aligned as per the distinct curriculum identified by the SeisTutor.

Table 3-2 Nomenclature

Symbol	Definition
DKB_{SDI}	Knowledge of Seismic Data Interpretation Subject Domain
LS_{SDI}	a pool of knowledge capsules or pedagogy style
LT_{SDI}	a collection of learning or subject topics
SST_{SDI}	set of subject sub-topics
STR_{SDI}	describes the association between topics
$SSTR_{SDI}$	defines the association between the sub-topics

ST_{Update}	update function utilized by the domain or subject experts
SST_{Update}	subject sub-topic update function utilized by the domain or subject experts

Definition:

A formal representation of a domain or subject knowledge in SeisTutor is defined as follows:

$$DKB_{SDI} = < LS_{SDI}, LT_{SDI}, SST_{SDI}, STR_{SDI}, SSTR_{SDI}, ST_{Update}, SST_{Update} > \qquad (3.1)$$

$LS_{SDI} = \{PS_1, PS_2, PS_3 \ldots\ldots\ldots, PS_{12}\}$ It is a pool of knowledge capsules or pedagogy style, depending upon the identified pedagogy style one chosen among them.

$LT_{SDI} = \{LT_1, LT_2, LT_3, \ldots\ldots\ldots\}$ It is a collection of learning or subject topics covered during the learning session.

$SST_{SDI} = \{ST_1, ST_2, ST_3, \ldots\ldots\}$ It is a set of subject sub-topics used to illustrate the topic thoroughly.

$STR_{SDI} = \{STR_1, STR_2, STR_3, \ldots\ldots\}$ Subject topic relation describes the association between topics (prerequisite, part of).

$SSTR_{SDI} = \{SSTR_1, SSTR_2, SSTR_3, \ldots\ldots\}$ Subject sub-topic relationship defines the association between the sub-topics. Here association indicates how one sub-topic is associated (prerequisite, part of) to other sub-topics.

ST_{Update}: It is a subject topic update function utilized by the domain or subject experts to perform the required revisions in the course coverage plan.

SST_{Update} : It is a subject sub-topic update function utilized by the domain or subject experts to perform the required revisions in the learning material.

3.2.2.3. Domains of Learning

As per Benjamin Bloom, learning is everywhere, one can use their mental skill, develop an attitude and acquire physical skills based on their skill used to perform activities [93]. Bloom classifies the domain of learning into three different categories, i.e. Affective, Cognitive, and Psychomotor.

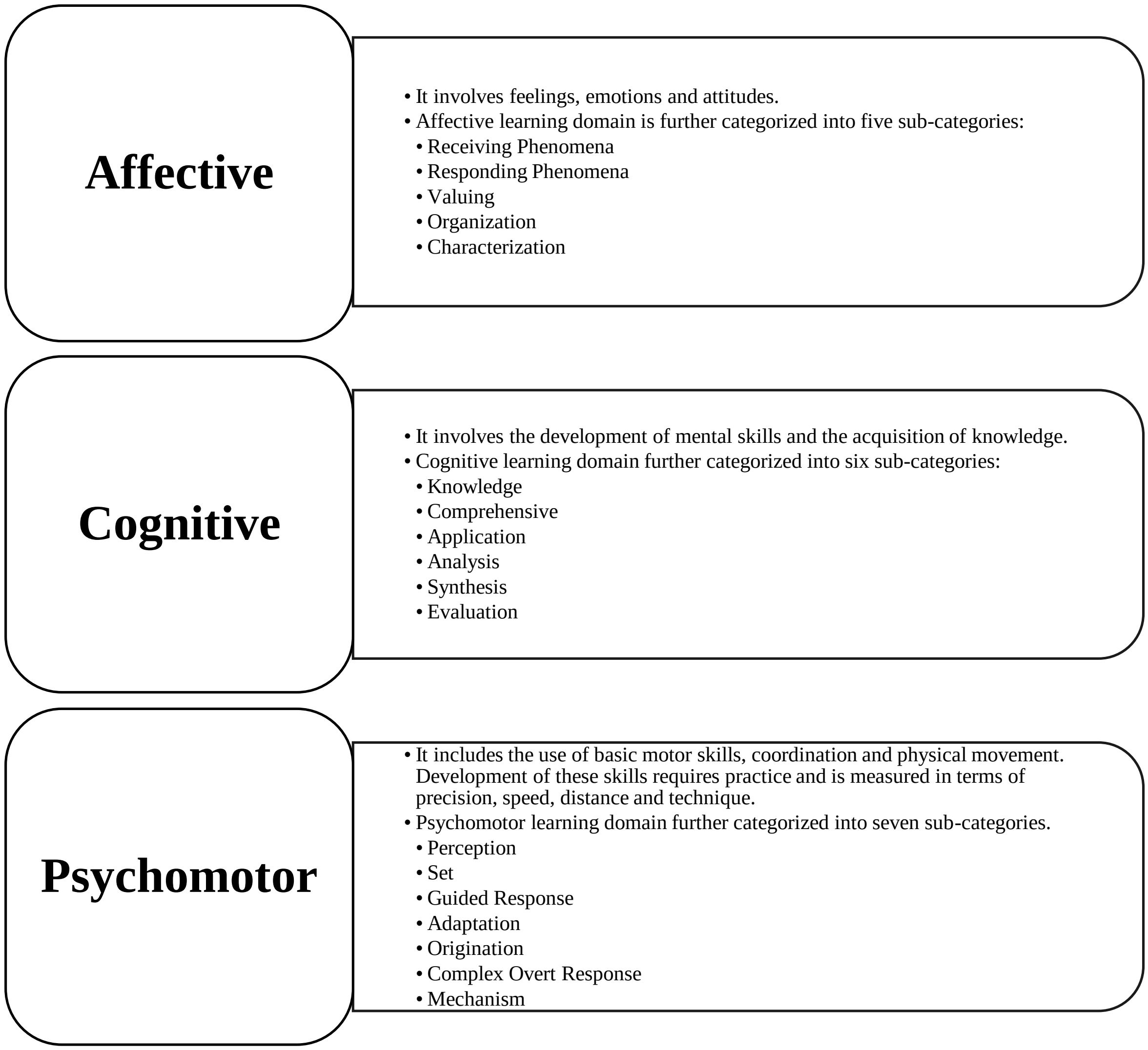


Figure 3-14 Learning Domain Categories.

For the current scope of work four learning styles are taken into the consideration, i.e. Imagistic, Intuitive, Acoustic and Active. The feature of these learning styles are formulated in table

Table 3-3 I2A2 Learning Styles

Learning Style (LS)	**Imagistic**	**Intuitive**	**Acoustic**	**Active**
Key Terminologies	Learning through perceiving	Learning through an understanding of the written word	Learning through hearing	Learning through accomplishment
Interactive Multimedia	Flowcharts, diagram, and videos	Written paragraph, written notes, and Action charts.	Listening	Hand-on Exercise

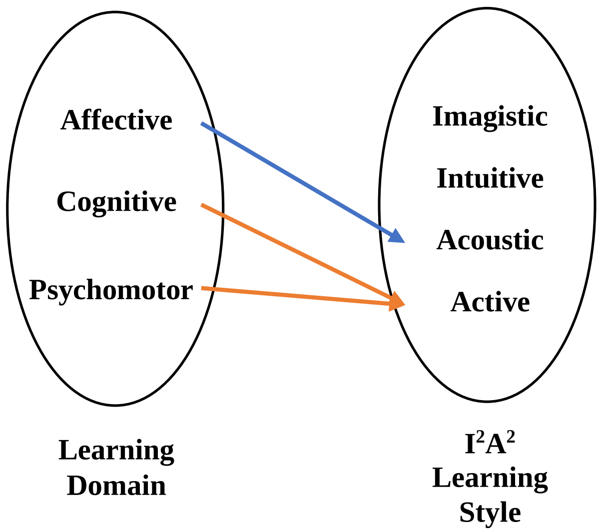


Figure 3-15 one to one mapping between the Learning Domain and the I2A2 Learning Style.

Figure 3.15 is showing how these learning domains are related to the incorporated learning styles.

Summary

This chapter presents the distinct features of implicit and explicit knowledge. Establishing the domain of Seismic Data Interpretation, as an experiential domain, it describes the steps involved in the accumulation of tacit knowledge, their characterization, and details the transformation of tacit-to-explicit-to-tutor-able. The tutoring material laid into a course delivery pattern comprising of 4 weeks and its execution through SeisTutor is described. The content has been organized into topics and subtopics in the week-wise pattern demonstrated in this chapter. Finally, an adaptive knowledge base is developed, that comprises of twelve knowledge capsules.

The next chapter covers, Pedagogy Model with the design and implementation of its, sub-modules, the Custom-Tailored Curriculum Sequencing Module, the Emotion Recognition Module, and the Performance Analyzer Module.

Chapter 4 : Design and Development Methodology of Pedagogy Model

This chapter introduces the detailed design of SeisTutor and the adaptive features incorporated in the Pedagogy Model. This is followed by an in-depth discussion of the adaptive features that are, Custom-Tailored Curriculum Sequencing module, Tutoring Strategy recommendation module, and Learner Performance Analyzer module (emotion recognition module and the degree of understandability). The emotion recognition module is used to keep track of learner emotions while the degree of understandability module is used to determine the learner degree of understanding after the completion of the learning session. The overall performance and activity of the learner is visualized in the form of a progress report.

4.1 Pedagogy Model

The pedagogy model is the brain of ITS, as it is responsible for making strategic decisions throughout the learning sessions. A strategic decision includes, identification of tutoring strategy, recommendation of an exclusive course coverage plan, gauging performance parameters, and analyzing the post-tutoring measures (learning gains, learner's emotional state throughout learning, the degree of understandability). It recommends the course structure, tailoring the representation of learning material depending upon the information captured in the learner model. This model comprises of three adaptation features, such as the Custom-Tailored Curriculum Sequencing module, Tutoring Strategy Recommendation, and Learner Performance Analyzer module, which have been built into it, to facilitate customized tutoring to the learner.

4.2.Proposed Architecture and Work Flow of SeisTutor

The execution is depicted in different phases (See Fig. 4.1). The pre-tutoring phase, also termed the Initial Assessment phase, is detailed below.

Firstly learner has to create learner account by registering themselves with the SeisTutor. As soon as a learner account is created, learners are asked to sign in to their account and undergo a pretest. The pretest is the inescapable pre-assessment test, without which learners are not allowed to proceed with the learning session. This test further opens up the way for learner to get tutored as per individual learning style and learning level attributes (termed as Tutoring Strategy).

The learner is put through a pretest, which provides a set of questions under two test categories – Domain Knowledge Test and Learning Style Test. Domain Knowledge Test comprises of 20 problems (questions). The Domain Knowledge Test is designed, in such a manner that the outcome of this test reveals two characteristics of the learner. One is the learner's competency (indicative of learner's grasping comfort), and the other is, learners' prior knowledge about the subject domain, and the outcome is referred as 'Learner Level'. Learning Style Test comprises 18 problems (questions). This set is referred to as the 'Learning Style Question Pool'.

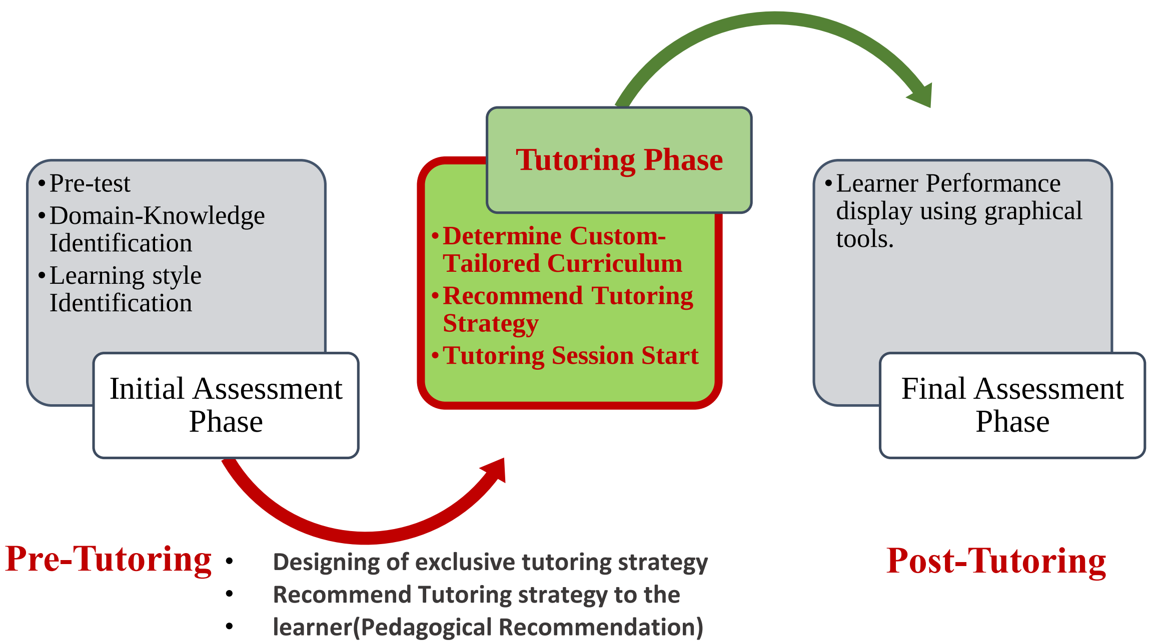


Figure 4-1 Architecture of SeisTutor

As per the scores of Domain Knowledge Test, the profiles, 'Beginner', 'Intermediate' or 'Expert' are allotted to the learner. Thereafter, the Leaner Level is alternatively referred as 'Learner Profile' in this work. The scores of 'Learning Style Test' are mapped with the Learning Styles, Imagistic, Intuitive, Acoustic and Active. Thus, pre-test once conducted for the learner generates output, translated as the learner's Learning Profile and Learning Style. This is the output of the pre-tutoring phase.

The combination of Learning Style and Learner Profile, is referred here, as Pedagogy Style. The Pedagogy Style governs the tutoring mechanism for the learner, and hence it is termed as the Tutoring Strategy, which is individualistic for the given leaner.

Presented below is an example, describing the process of determination of Tutoring Strategy, as per the pre-test scores

Assuming Learning Style Test score of the learner, is: Imagistic =9, Acoustic =3, Intuitive = 5, Active = 8 and the level of learner (as per scores of Domain Knowledge Test, and thereof, the allotment of the profiles)), is Beginner = 9, Intermediate = 4, Expert = 7. With the combination of both the test scores in increasing order, a list of pedagogy styles is listed and maintained by SeisTutor as a priority queue.

In this example, in the pretest, the level of the leaner was obtained as ‘Beginner’. As, per the outcome of the Learning Style Test, the Pedagogy Styles are listed Priority-wise, as: {(Imagistic-Beginner, 1), (Active-Beginner, 2), (Intuitive-Beginner, 3) and (Acoustic-Beginner, 4)}, indicating the Imagistic-Beginner combination is at the top of the list, followed by the combinations, Active-Beginner, Intuitive-Beginner, and Acoustic-Beginner in this order.

Thus, in this pretest case, the learner appears to be more of a 'Beginner' in terms of Level and having a higher preference for 'Imagistic' Learning Style than any other style. The 'Beginner + Imagistic' pedagogy style is identified to be executed for him/her.

Further, the prior knowledge of the learner, which is indicative of how much the learner knows, before he/she formally proceeds with the learning is also assessed through DKT, and is used in designing the Custom-Tailored Curriculum detailed in the next section of this chapter. Accordingly, an exclusive tutoring strategy, is devised by SeisTutor, with an exclusive course coverage plan, comprising the specific topics and sub-topics aligned exclusive for the learner.

4.2.1 Custom-Tailored Curriculum Sequencing Model

Generally two kinds of information are employed during face to face tutoring scenario, i.e. understanding the learner requirements (grasping level, preferred style of learning), accordingly the teaching strategy is devised.

The most desirable feature of a teacher is to adjudge the psychology (emotion or expression) of the learner and accordingly adapting the teaching style. As per the learner preference, the primary aspect of adapting is to select the most optimal course coverage plan, as a critical response to the learner's prior knowledge (Zhu and Cao 2008) [89].The selection of the most optimal learning path is depiction of ideal human cognitive intelligence in classroom teaching. This cognitive intelligence has been developed in SeisTutor.

In a traditional ITS architecture, the learner model gauges the learner characteristics by observing the learner’s activities throughout the learning sessions. The pedagogy model collaboratively works with the learner model, which determines a custom-tailored course coverage plan for the learner.

In SeisTutor, the Curriculum Generator Module has been developed, that utilizes the performance measures of the learner in the pretest and designs the exclusive curriculum (See Fig. 4.2).

The devised curriculum is appropriate for learning, as it adapted to the learner as per his/her competency level and preferences.

The learning session is planned to proceed with the recommended curriculum. The curriculum recommendation is the list of topics and subtopics identified from the knowledge pool and aligned in a specific sequence. The sequencing of topics and sub-topics as per the identified curriculum is known as 'learning path.' In this scope of work, the exclusive curriculum is determined using the 'Bug-Model' technique.

The Domain Knowledge Test, as mentioned above, is presented before commencing the learning session. Every question in this test is associated with the subject topics/sub-topics by a tag that functions as an identifier for the subject topic/sub-topic. The course generator examines every response provided by the learner. The incorrect responses by the learner are categorized as 'bug.'

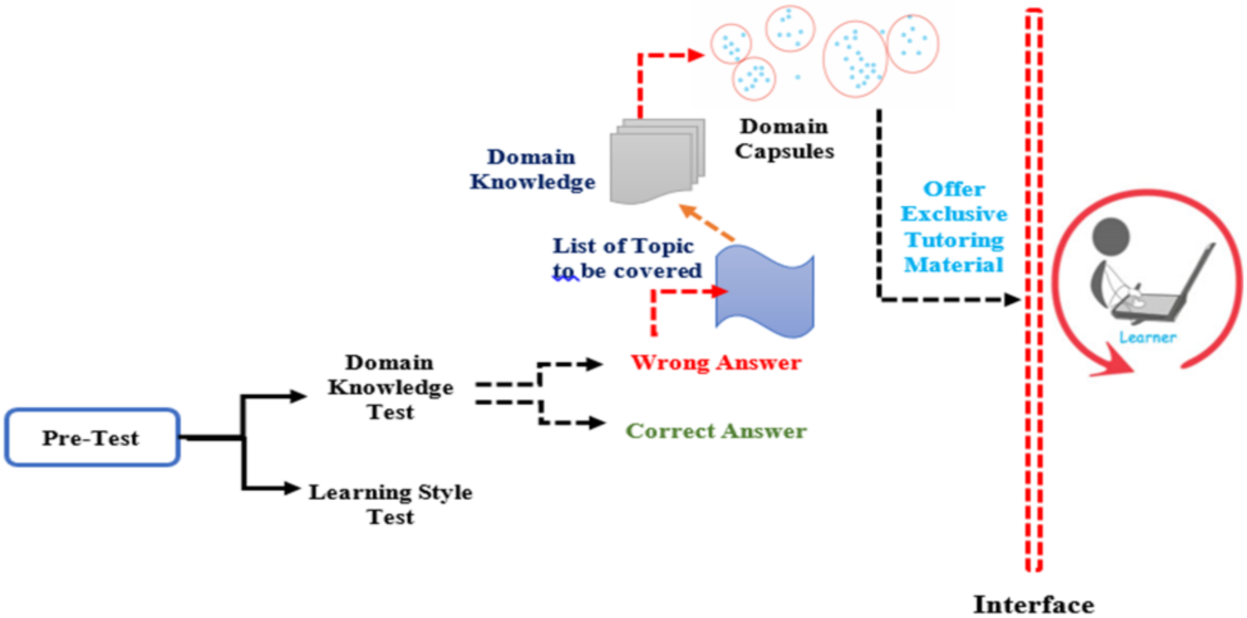


Figure 4-2 Working of proposed CTCSS Module

Subsequent to the completion of Domain Knowledge Test, Course Generator can generate the list of 'bugs,' wherever the learner provided incorrect responses. This list is a collection of topics/sub-topics, that learners may not be having a very clear understanding. This leads the Course Generator to recommend the learning path which includes these topics or sub-topics, directing the learner to gain comfort and mastery by offering repetition, re-emphasis, and additional clarity on the subject topics / subtopics where the learner currently holds less understanding. This is referred as Custom-Tailored Curriculum Sequencing.

4.2.1.1 Mathematical justification of Custom-Tailored Curriculum Sequencing Module

Table 4-1 Nomenclature

Symbol	Description
ST	List of topics to be discussed
$DKT\ This\ is\ _{Q}$	The questionnaire asked in Pretest.
$DKT_{Correct}$	Correct response
DKT_{wrong}	Incorrect response
$Curr_{Topic}$	Topic to be learned
st_1	Introduction
st_2	Seismic Waves
st_3	Reflection Seismology
st_4	Survey Types
st_5	Analog and Digital Recording Equipment's
st_6	Horizon Correlation
st_7	Faults in Petroleum Provinces
st_8	Stress & Strain
st_9	Seismic Expression of Faults
st_{10}	Interpretation of Fault data and 3-D data
st_{11}	Velocity Interpretation
st_{12}	Hydrocarbon Indicators

Let us consider ST as the list of topics to discuss during the learning session.

$$\boldsymbol{ST} = \{\boldsymbol{st_1}, \boldsymbol{st_2}, \boldsymbol{st_3}, \dots \dots \dots \dots \boldsymbol{st_{12}}\} \qquad (4.1)$$

Let us consider DKT_Q is the pool of questionnaire asked in Domain Knowledge Test (DKT) (Pretest).

$$\boldsymbol{DKT_Q} = \{\boldsymbol{dktq_1}, \boldsymbol{dktq_2}, \boldsymbol{dktq_3}, \dots \dots \dots \boldsymbol{dktq_{12}}\} \qquad (4.2)$$

Then,

$$\boldsymbol{DKT_Q} \in \boldsymbol{ST} \qquad (4.3)$$

Eqn. 4.3 specifies that each question that is asked during DKT is associated with the list of topics detailed to discuss.

Note:

The association between topics and questions can be many-to-one and one-to-one, for the ease of illustration and understanding one-to-one mapping is considered and demonstrated below (See Fig. 4.3).

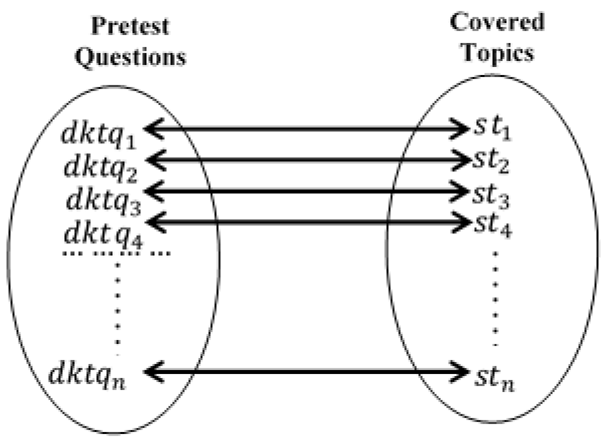


Figure 4-3 One-to-one mapping state

Let us consider $DKT_{Correct}$ as the list of questions responded correctly, and $\boldsymbol{DKT_{wrong}}$ the list of questions responded incorrectly.

$$\boldsymbol{DKT_{Correct} = \{dktc_1, dktc_2, dktc_3, \ldots \ldots \ldots dktc_{12}\}} \tag{4.4}$$

$$\boldsymbol{DKT_{wrong} = \{dktw_1, dktw_2, dktw_3, \ldots \ldots \ldots dktw_{12}\}} \tag{4.5}$$

Let us consider that the learner provides correct responses to (DKT_Q) 20 % of questions.

As $\boldsymbol{DKT_{correct} \in DKT_Q}$ **and** $\boldsymbol{DKT_{correct} \subseteq DKT_Q}$ (4.5)

$$\boldsymbol{DKT_{correct} = \{dktc_3,\ dktc_6,\ dktc_{10}\}} \tag{4.6}$$

Then 80 % of questions DKT_Q belong to the list of incorrect responded questions.

$$\boldsymbol{DKT_{wrong} = \left(DKT_Q - DKT_{correct}\right)} \tag{4.7}$$

i.e.

$$\boldsymbol{DKT_{wrong} = \{dktw_1,\ dktw_2,\ dktw_4,\ dktw_5,\ dktw_7,\ dktw_8,\ dktw_9,\ dktw_{11},\ dktw_{12}\}} \tag{4.8}$$

Similarly, $\boldsymbol{DKT_{wrong} \in DKT_Q}$ **and** $\boldsymbol{DKT_{wrong} \subseteq DKT_Q}$ (4.9)

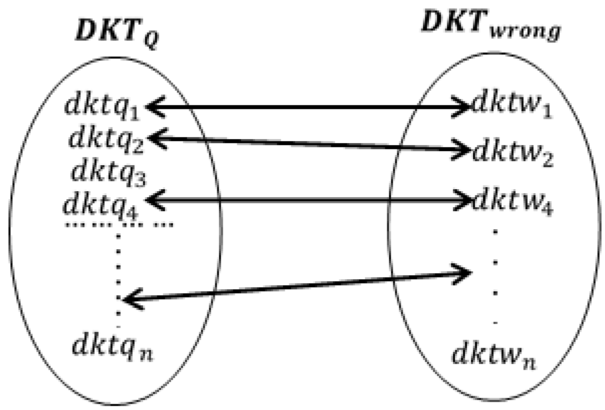


Figure 4-4 One-to-one mapping between incorrectly responded and domain knowledge questions.

The DKT_{wrong} list is made up of questions that are incorrectly responded by the learner from the pool of questionnaire DKT_Q (See Fig.4.4).

Above-mentioned in Eqn. 4.3 that $\boldsymbol{DKT_Q} \in \boldsymbol{ST}$

Therefore by transitivity law of algebra, i.e., if Set $X \in Y$, and Set $Y \in Z$, then $X \in Z$ or $X \in Y \in Z$

Thus, $\boldsymbol{DKT_{wrong}} \in \boldsymbol{DKT_Q} \in \boldsymbol{ST}$ (4.10)

$\boldsymbol{ST} = \{\boldsymbol{st_1}, \boldsymbol{st_2}, \boldsymbol{st_4}, \boldsymbol{st_5}, \boldsymbol{st_7}, \boldsymbol{st_8}, \boldsymbol{st_9}, \boldsymbol{st_{11}}, \boldsymbol{st_{12}}\}$ (4.11)

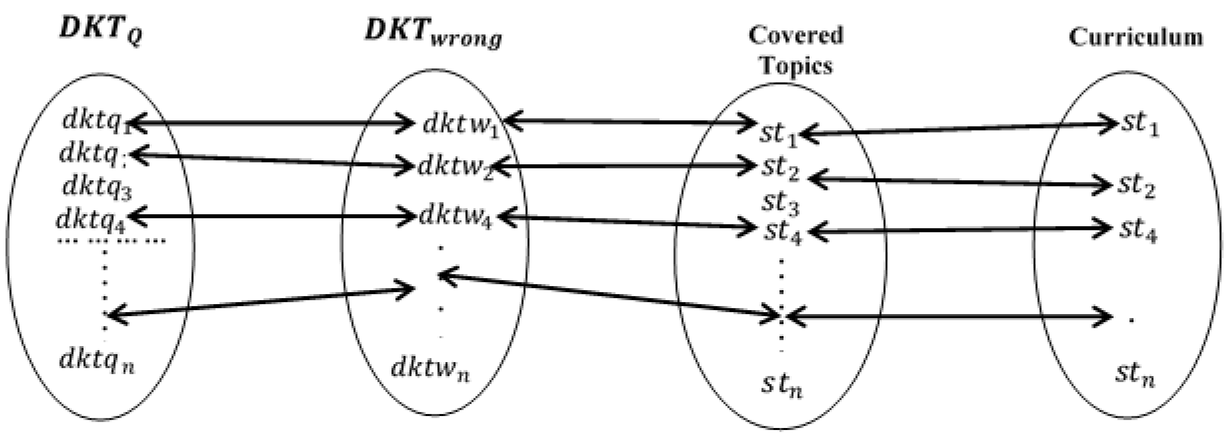


Figure 4-5 Curriculum designing

As per Eqn. 4.11 and 4.12, custom-tailored curriculum design is determined by SeisTutor. The mathematical proof is demonstrated in Fig. 4.5. The algorithm for the custom-tailored curriculum sequencing using the bug model is presented below.

4.2.1.2 Algorithm

Input: Outcomes of Domain Knowledge Test

Output: Exclusive curriculum design for the learner

Begin

1. Retrieve the answers opted by the leaner for the given set of questions DKT_Q in a variable $DKT_{RT} = \{QR_1, QR_2, QR_3, \dots\dots\dots, QR_n\}$. Where RT is a set which encloses, learner's responses, DKT_Q is the set of asked questions, and $QR_1, QR_2, QR_3, \dots\dots\dots, QR_n$ is individual learner responses.
2. Matching operation performed between the received results and the actual copy of answers, which stored in the database. $AC = \{QA_1, QA_2, QA_3, \dots\dots\dots, QA_n\}$. Where AC is a set that encloses correct responses and QA_1, QA_2, $QA_3, \dots\dots\dots, QA_n\}$ is the corresponding correct answers.
3. Separate sets of correct responses $DKT_{Correct}$ and incorrect responses DKT_{wrong} created.

    3.1. do
    3.2. {
    3.3. $if\ (QR_i == QA_i)$
    3.4. {
    3.5. $DKT_{correct} = dktq_i$;
    3.6. }
    3.7. $else$
    3.8. {
    3.9. $DKT_{wrong} = dktq_i$;
    3.10. }
    3.11. $i++$;
    3.12. } while $(i \leq n)$; // $where\ n\ is\ the\ number\ of\ questions\ asked\ in\ Pre - Knowledge\ Pretest$
4. Step 2 and 3 will repeat for all the response until while condition met.
5. DKT_{wrong} Sets are taken into consideration and perform a mapping operation between the topics covered and DKT_{wrong} sets.

    5.1. $for\ (k = 1; k \leq n; k++)$
    5.2. {
    5.3. $for\ (l = 1; l \leq n; l++)$
    5.4. {
6. $If\ \left(DKT_{wrong_k} == QW_k == ST_l\right)$ *// where QW is a set which encloses the labels (that directly links to the topics) and* $QW = \{QW_1, QW_2, QW_3, \dots\dots\dots, QW_n\}$ *are the respective labels associated with the questions.*

    6.1.
    6.2. {
    6.3. $ST = st_l$;
    6.4. }
    6.5. $else$
    6.6. {
    6.7. $continue$;
    6.8. }
    6.9. }
    6.10. }
7. ST Set consists of the course collection, which is exclusively designed for the learner by the SeisTutor.

End

4.2.2 Tutoring Strategy Recommendation

As in case of traditional face to face teaching, the content delivery to the learners comprises of the human tutor understanding their profile, learning style and accordingly devising the strategy to deliver content. Similarly, the tutoring by SeisTutor is based on key attributes of the learner, the Learner Profile, Learning Style and the prior knowledge assessed through Bug Model. The tutoring strategy is termed as Custom-tailored Curriculum Tutoring Strategy. This comprises of all input parameters obtained from the pre-tutoring phase. (see Fig. 4.6, Fig. 4.7, and Fig. 4.8). Table 4.2, 4.3, 4.4 and Table 4.5 describe the input parameters involved)

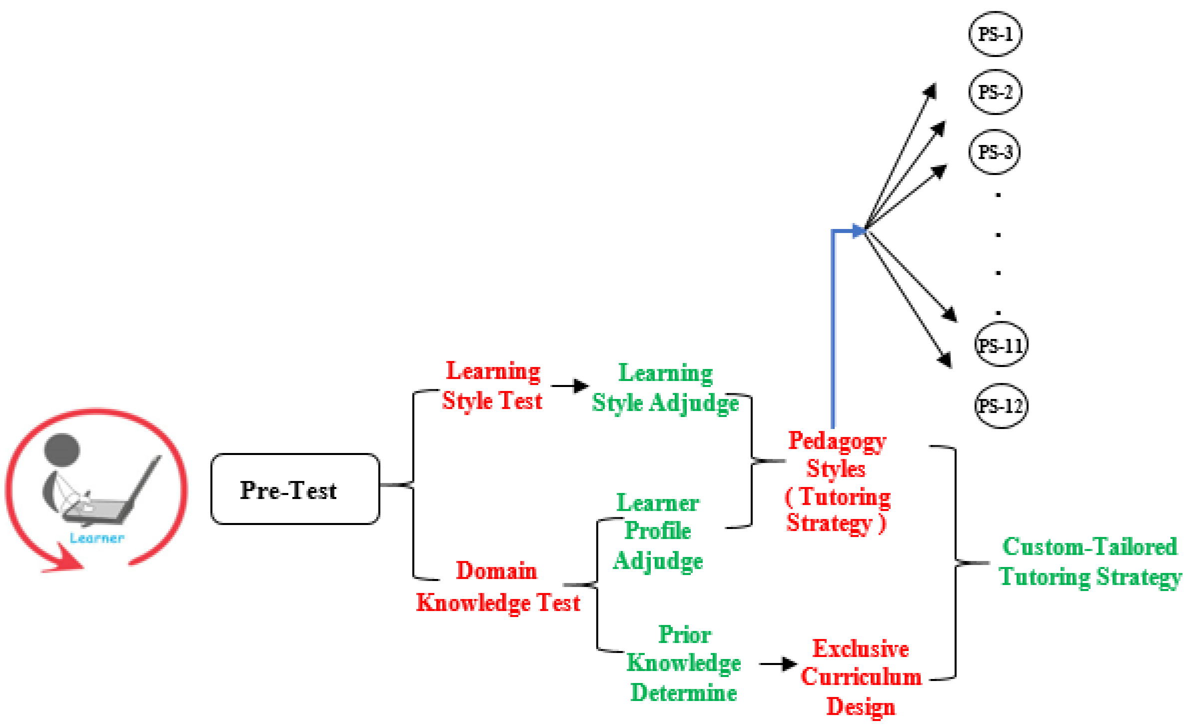


Figure 4-6 Conceptual flow of Tutoring Strategy (Instructional Strategy) computation

Table 4-2 Parameters for Tutoring Strategy Computation

Parameters	Values			
Learner Profile (LP)	Beginner	Intermediate		Expert
Learning Style (LS)	Imagistic	Intuitive	Acoustic	Active
Prior-Knowledge (PK)	List of topics/sub-topics identified based on bugs.			

Table 4-3 Learning Profile attributes

Parameters	Values		
	Value = 0	Value = 1	Value = 2
Learner Profile (LP)	Beginner	Intermediate	Expert
Difficulty Level	Easy (Simple)	Average (Moderate)	Tough (Proficient)
Features	More comprehensive illustration.	Less comprehensive illustration.	Precise (to the point)

Table 4-4 Learning Style attributes

Parameters	Values			
	Value = 0	Value = 1	Value = 2	Value = 3
Learning Style (LS)	Imagistic	Intuitive	Acoustic	Active
Key Terminologies	Learning through perceiving	Learning through an understanding of the written word	Learning through hearing	Learning through accomplishment
Interactive Multimedia	Flowcharts, diagram, and videos	Written paragraph, written notes, and Action charts.	Listening	Hand-on Exercise

Table 4-5 Structure of Pedagogy Styles in 'SeisTutor'

S.N.	Pedagogy Styles (PS)	Learner Profile (LP)	Learning Styles (LS)			
			Imagistic	Intuitive	Acoustic	Active
1.	PS1	Beginner	✓			
2.	PS2	Beginner		✓		
3.	PS3	Beginner			✓	
4.	PS4	Beginner				✓
5.	PS5	Intermediate	✓			
6.	PS6	Intermediate		✓		
7.	PS7	Intermediate			✓	
8.	PS8	Intermediate				✓
9.	PS9	Expert	✓			
10.	PS10	Expert		✓		
11.	PS11	Expert			✓	
12.	PS12	Expert				✓

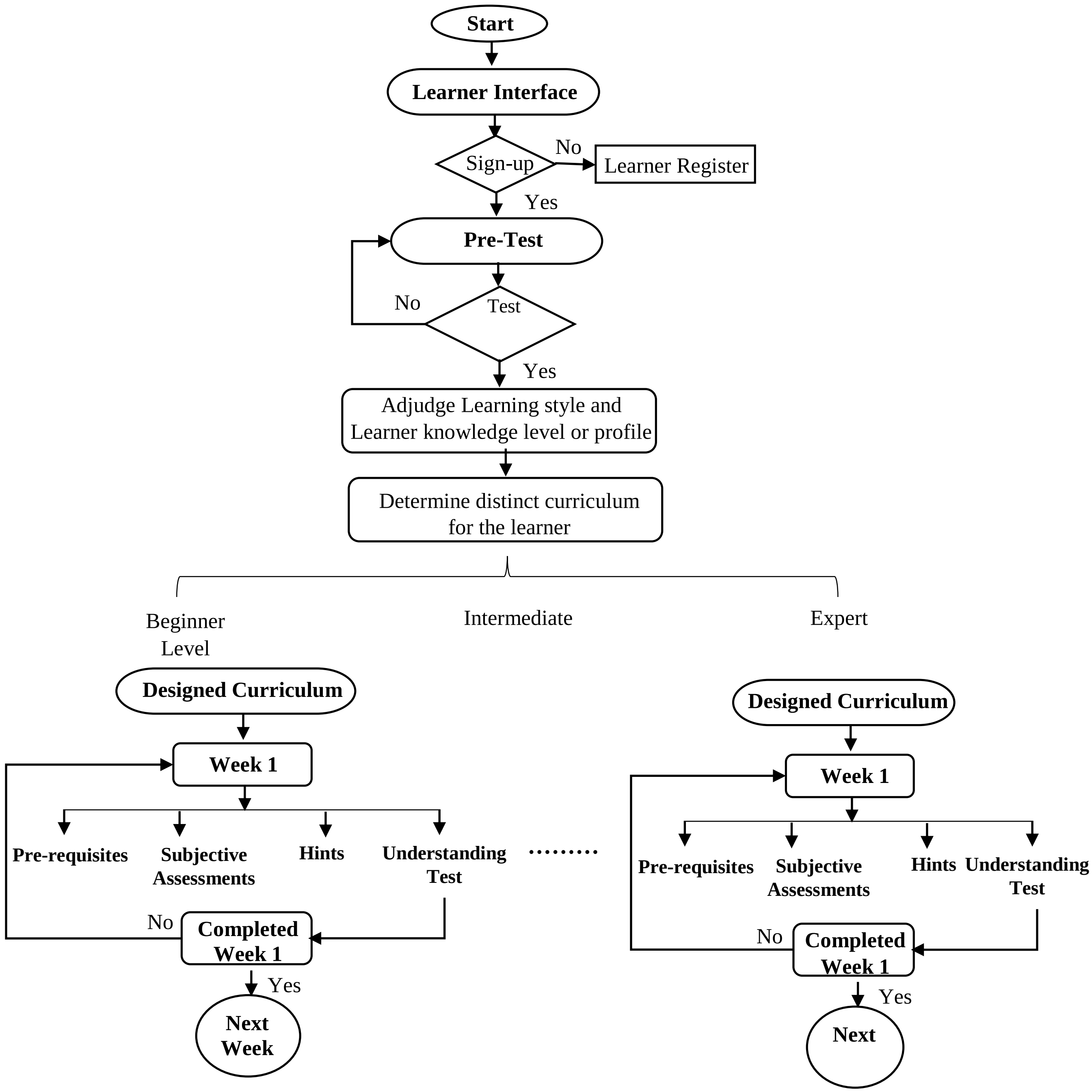


Figure 4-7 Design of Selection of Tutoring Strategy (TS)

Twelve combinations of various pedagogy styles have been developed. Each blend is represented as a distinct strategy, and every plan is pre-characterized based on the inputs of tutoring parameters for pre-tutoring phase. Each combination is mapped with the specific level and style content to provide to the learners.

The twelve pedagogy styles (PS_1, PS_2…, PS_{12}), each is combination one Learner Profile and one Learning Style (see Table 4.2, 4.3, 4.4, and Fig 4.6) and is mapped to its content, that embodies the said characteristics of respective profile and preferred style of the learner. Based on the prior knowledge of the learner, in SeisTutor, as per the algorithm discussed in section 4.2.1.2, alignment of content and designing of exclusive curriculum (course coverage plan) in done for the learner.

Thus, the developed custom-tailored curriculum tutoring strategy is available to be recommended by the SeisTutor. The design for selecting a tutoring strategy for the different groups of the learners is presented in Figure 4.8.

The Second Phase is the Tutoring Phase. In this phase, the learner gets started with the tutoring session, as per the initially identified tutoring strategy, and learner activities are captured. Activities include recording and analysis of psychological and non-psychological parameters. Learner Psychological parameters are the learner's emotions during the ongoing tutoring sessions. In contrast, non-psychological parameters are the performance in the week-wise assessment, computed through, 'number of question attempts, number of correct answers, number of hints taken, and time taken.' One checkpoint, usually at the end of each week, is incorporated, that offers to change tutoring strategy (in a user-driven [learner can opt for the flip] or system-driven manner SeisTutor decides and flips based on learner performance measures). The tutoring strategy can be altered (flipped), only once during the entire tutoring session. The decision of changing pedagogy style, is effected through assignment of the next pedagogy style in the priority queue. This decision is taken, based on the performance parameters of the learner, during the ongoing tutoring session. In other words, the pedagogy style of the learner is altered when the learner is low on the performance in the current pedagogy style, indicating that the learner may not be comfortable with the current pedagogy style, calling for a change of the tutoring strategy.

Performance parameters play a vital role in understanding the comfort level of the learner. Their monitoring during the ongoing learning forms the basis to trigger the change of tutoring strategy, as applicable.

The SeisTutor mimics the behavior of the human tutor, i.e. by offering the learning material as per learner's prior or previous knowledge, preferred learning style and learner grasping levels (obtained in pre-tutoring phase) bringing in the adaptive feature. During ongoing tutoring based on numeric (quantitative) performance parameters, quantitative values such as the degree of understanding, learner emotional state and learning gain, are being determined.

The third phase is the Post Tutoring Phase. In this phase SeisTutor generates the learner progress report, which includes learner week-wise measures for quiz performance, emotions, degree of understanding of learned concepts, session details, time spends on topics, Learning Gain and Dynamic Profile (Profile Shift (before and after learning))

4.2.3 CNN based Emotion Recognition Module

This **Emotion** recognition module gets triggered when the learner starts the learning session (shown in Figure 4.8). As illustrated in Figure 4.7, as soon as the learner begins the learning session, CNN based emotion recognition module is instantiated (see Figure 4.8). The CNN based emotion recognition module is implemented using machine learning techniques of artificial intelligence, i.e. Convolution Neural Network (CNN). From the several studies on Facial Expression Recognition (FER) literature, it has been found that convolution neural network is best for face pose, face location and facial scale deviations [90] [91]. Therefore, for emotion recognition, nine layer based CNN module is developed. The work flow of CNN based emotion recognition module is shown in Fig. 4.8. The emotion recognition module captures the snap of the learner through webcam, which is further processed by the CNN based emotion recognition module, and determines the facial emotion of the learner. The determined emotion is saved for future analysis (Phase 1: Evaluation of Reaction). The whole process of gathering emotion states is repeated until the learner completes all the learning content (topics) associated for all the week.

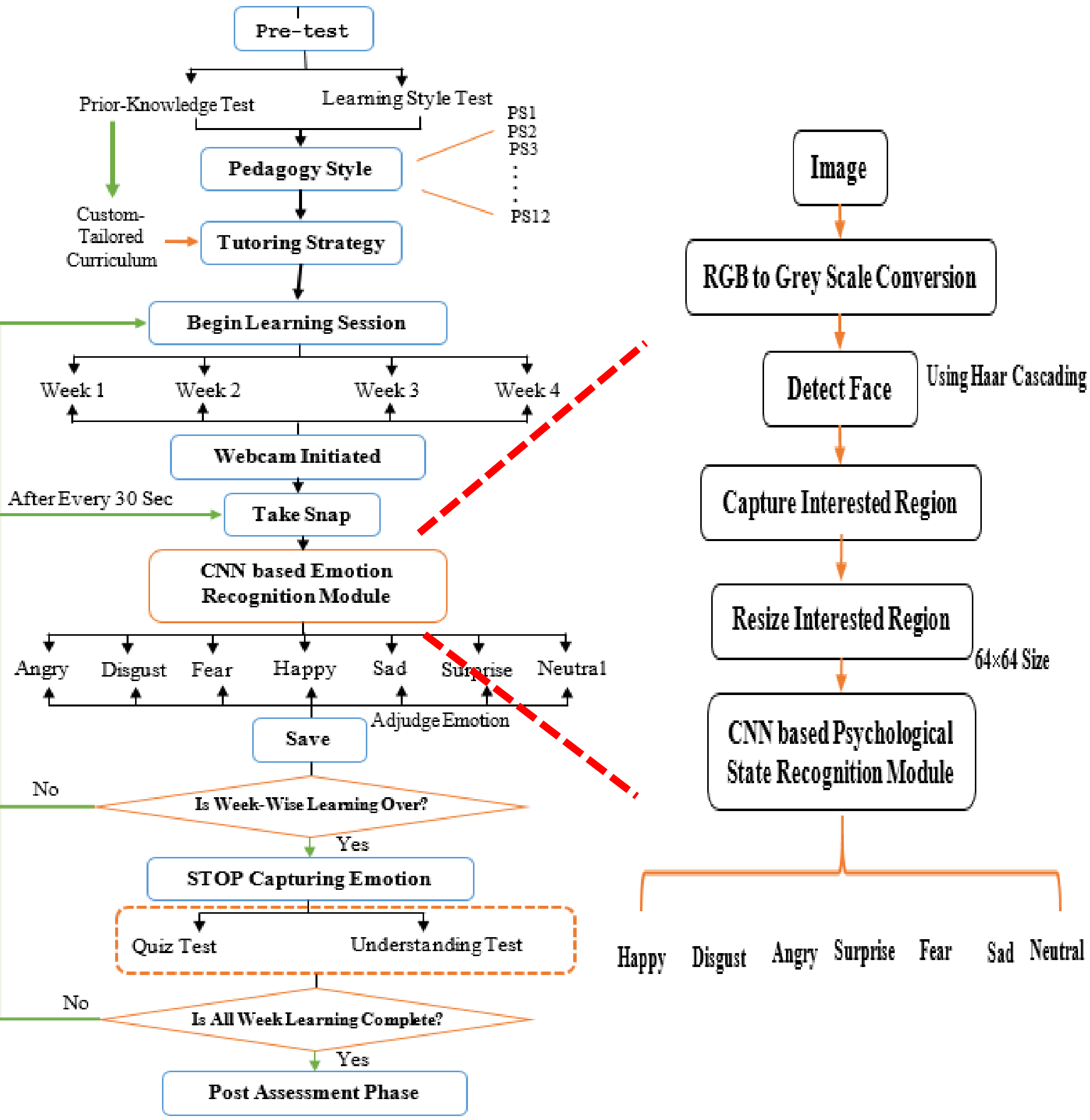


Figure 4-8 CNN based Emotion states Recognition Module

Emotional state, i.e., facial emotion recognition, involves two steps.

1) Face Detection
2) Emotion Detection

To accomplish this proposed model, it follows two techniques:

1) Haar Cascade classifier: It identifies the frontal face or affected region in an image. There are other techniques to do the same task, but Haar Cascade is faster in real-time.
2) Xception CNN Model: For emotion recognition, CNN architecture used in which $(48 * 48\ Pixels)$ of the bounded face is taken as an input and based on the probabilities, it predicts the emotion.

Data-Set

The dataset for training and validation processes are gathered from the Kaggle website [92]. The dataset contains grayscale face images of $(48 * 48\, pixels)$. The primary task is to classify the face image on the basis of seven kinds of emotions (Happy =3, Sad=4, Surprise=5, Neutral=, Angry= 0, Disgust = 1, Fear = 2). There are 35,888 samples in the FER2013 dataset.

The following techniques are used for the training of CNN model.

Data Augmentation: This technique is used when the training data is not adequate to learn the image features. It performs operations like normalization, cropping, rotation, zoom, flip, and shear on training dataset.

Kernal regularizer: During optimization, it puts penalties on layers, these penalties further fused with a loss function. L2 regularization is augmented in CNN.

Batch Normalization: It is used for normalizing the activation of the preceded layer. It is used to increase the speed of the training process.

Global Average Pooling: It is used to reduce feature maps (computing average of all feature map elements) into a scalar value.

Depth-Wise Separable Convolution: It reduces the computational cost (decreasing the number of parameters) in comparison with the standard convolution layer.

4.2.3.1 Case-Wise Response of CNN-based Emotion Recognition Module.

Case 1: Learner created his/her Learner account and sign in to the SeisTutor.

System Behavior: Learner psychological states are not recognized by the CNN-based Emotion Recognition Module immediately after learner logs on to the learner account.

Case 2: Learner undergoes Pretest.

System Behavior: Learner psychological states are not recognized by the CNN-based Emotion Recognition Module during pre-assessment test (pretest).

Case 3: Learner begins the Learning session by accessing lesson under week (1 to 4) but does not complete the lesson.

System Behavior: The CNN-based emotion recognition module starts capturing the learner emotions as the learner accesses lessons under week (1 to 4) and finishes by clicking on “Mark as Completed” button. The system takes as the learner has completed the lesson. Successively as the learner, continues lesson after lesson across weeks, the learner emotions are captured until the session is active.

Case 4: Learner begins the Learning session by accessing lesson under week (1 to 4) but does not finish the lesson and the session abruptly closes.

System Behavior: if this scenario is encountered then the system does not present the learner emotions, as no records of the same is maintained.

Case 5: Learner begins with the Learning session and continues learning lesson after lesson but does not click the "Mark as Complete" button.

System Behavior: if this scenario is encountered then the system continues to capture learner emotions until the session is active.

Case 6: Learner begins with the Learning session and continues learning lesson after lesson and clicks on "Mark as Complete" button of the particular lesson.

System Behavior: if this scenario is encountered then the system captures the learner emotions for that particular lesson.

Case 7: Learner begins the Learning session by clicking on a Lesson under week (1 to 4) but completed the lesson.

System Behavior: in this scenario, the system captures learner's psychological state for that particular lesson.

Case 8: Learner undergoes Performance Assessment Test (Quiz Test and Degree of Understanding Module).

System Behavior: Learner's emotions are not captured during Performance Assessment Test.

4.2.4 Learner Performance Analyzer Module

4.2.4.1.Degree of Understandability

The Degree of Understandability module aims to identify how effectively a learner understands the taught concepts. The word-based summary analysis is performed to assess in SeisTutor. The basic flow of this module is shown in Fig. 4.9.

The tutoring sessions are scheduled and executed in a week-wise pattern. After completion of the first week of the learning session, a subjective test has been implemented. This test asks the learner to enter his/her understanding of the learning content in the form of plain text (see Fig. 4.10). Further, these plain texts are split into sentences using stop words. There is a set of reference matrix, which includes the Main Reference Matrix and Co-Occurrence Reference Matrix. N-Gram Co-Occurrence Reference Matrix contains the N terms that describe the properties and features of the main reference matrix. Sub lexicons are in one to many relationships with the main lexicons. Learner Solutions compared with the Main Reference Matrix and make a separate matrix of both matched and unmatched text/words. Based on the matched terms, the level similarity measure is quantified (see Fig. 4.10). Now, based on matching lexicons from the main reference matrix, their associated N-gram Co-Occurences reference text is retrieved. Next step is to compare the N-gram Co-Occurences reference text with the learner solution and make a separate matrix of both matched and unmatched text. Based on the match, the N-gram Co-Occurrence similarity measure is quantified (see Fig. 4.11). Now from Eqn. 30, 31, and 32, the understanding scores (polarities) or the degree of understanding has been computed The purpose of making the unmatched matrix is to give necessary feedback to the learner, which notifies that the learner has not understood or covered these topics and suggest to revisit the specific topics. Based on the understanding score, polarities have been determined.

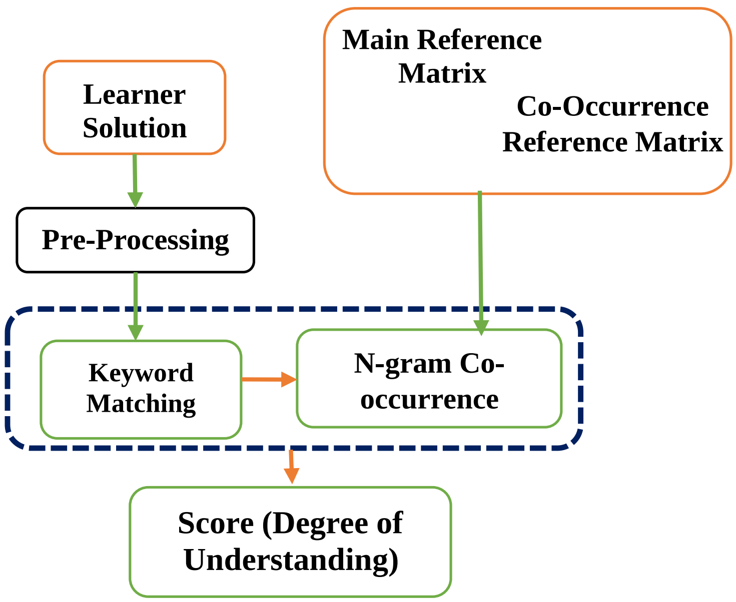


Figure 4-9 Flow Diagram of the proposed performance analyzer module

$$Polarities = \begin{cases} Above > 30\ \%\ Effective\ Impact \\ Dou < 30\ \%\ Negligible\ Impact \end{cases}$$

$$Subject: Seismic\ Data\ Interpretation$$

$$Opinion\ Holder: Participants\ of\ SeisTutor$$

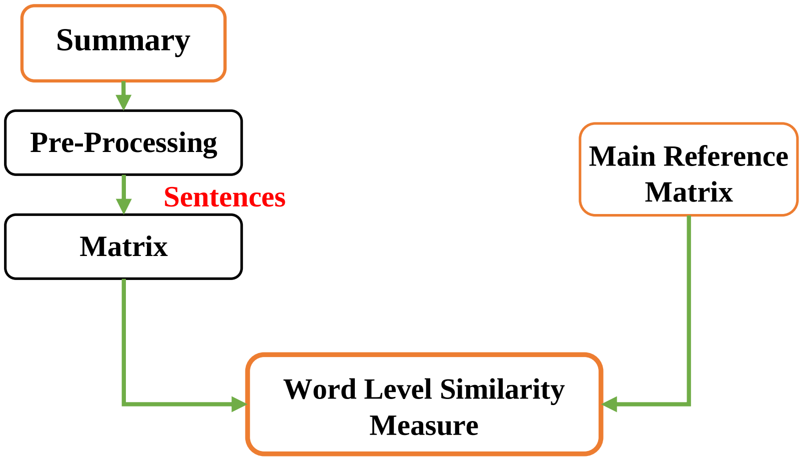


Figure 4-4-10 Step-Wise Execution of keyword matching technique

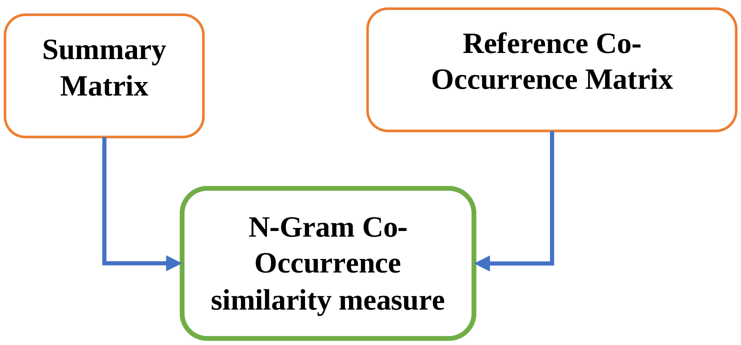


Figure 4-11 N-Gram Step-Wise Execution

Mathematical Justification of Performance Analyzer Module

Table 4-6 Nomenclature

Symbol	Definition
$\boldsymbol{W}$	It represents a week, as performance analyzer SeisTutor computes the degree of understanding.
$\boldsymbol{MK}$	Set of Main Reference Matrix.
$\boldsymbol{SK_{mk_i}}$	Set of Co-Occurrence Reference Matrix subsequence of words that carry in a sentence.
$\boldsymbol{X}$	Learners entered a summary of the learned concepts.
$\boldsymbol{ArrMatchList}$	It contains the words that are in the Main Reference Matrix.
$\boldsymbol{ArrResult}$	It contains the words which are not in both Main Reference Matrix and Co-Occurrence Reference Matrix
$\boldsymbol{SubMatchList}$	It includes the lexicon that is in both Main Reference Matrix and Co-Occurrence Reference Matrix
$\boldsymbol{NoTopicList}$	It contains the words that are not in the Main Reference Matrix.
$\boldsymbol{SMK_{mk_1}}$	Matched Co-Occurrence Reference Matrix
$\boldsymbol{Counter}$	A variable that counts the rewards when there is a match.

Let us consider MK is the Main Reference Matrix in W_k

$$\boldsymbol{W} = \{\boldsymbol{W_1}, \boldsymbol{W_2}, \boldsymbol{W_3}, \boldsymbol{W_4}\} \tag{4.12}$$

$$\boldsymbol{MK} = \begin{bmatrix} \boldsymbol{mk_1} \\ \boldsymbol{mk_2} \\ \vdots \\ . \\ \boldsymbol{mk_{10}} \\ \boldsymbol{mk_{11}} \\ \boldsymbol{mk_{12}} \end{bmatrix} \tag{4.13}$$

Let us consider SK is the Co-Occurrence Reference Matrix that illustrates functionality, feature & property about words in the Main Reference Matrix.

$$\boldsymbol{SK_{mk_1}} = \begin{bmatrix} \boldsymbol{mk_1} & \boldsymbol{sk_1} \\ \boldsymbol{mk_1} & . \\ \boldsymbol{mk_1} & \boldsymbol{sk_7} \end{bmatrix} \tag{4.14}$$

$$\boldsymbol{SK_{mk_2}} = \begin{bmatrix} \boldsymbol{mk_2} & \boldsymbol{sk_1} \\ \boldsymbol{mk_2} & . \\ \boldsymbol{mk_2} & \boldsymbol{sk_9} \end{bmatrix} \tag{4.15}$$

$$\boldsymbol{SK_{mk_3}} = \begin{bmatrix} \boldsymbol{mk_3} & \boldsymbol{sk_1} \\ \boldsymbol{mk_3} & . \\ \boldsymbol{mk_3} & \boldsymbol{sk_5} \end{bmatrix} \tag{4.16}$$

Similarly for, $\boldsymbol{SK_{mk_{12}}} = \begin{bmatrix} \boldsymbol{mk_{12}} & \boldsymbol{sk_1} \\ \boldsymbol{mk_{12}} & . \\ \boldsymbol{mk_{12}} & \boldsymbol{sk_8} \end{bmatrix}$ (4.17)

$$\boldsymbol{SK} \in \boldsymbol{MK} \tag{4.18}$$

Eqn. 4.19 indicates that there is a strong correlation between Co-Occurrence Reference Matrix and the Main Reference Matrix, which describes the fruitful information conveyed during learning sessions.

Let us consider the learner entered paragraph, further saved in X for further operation.

$$\boldsymbol{X} = \{" \qquad\qquad\qquad\qquad "\}\,\boldsymbol{;}$$

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x_{11}} & \cdots & \boldsymbol{x_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{n1}} & \cdots & \boldsymbol{x_{nn}} \end{bmatrix} \tag{4.19}$$

Suppose there are four lists named as
$ArrMatchmatrix, ArrResultmatrix, SubMatchmatrix, and\ NoTopicmatrix$

The next operation is to compare matrix X with the main reference matrix.

i.e., compare X with MK

----) if, there is a match, then add MK_i in $ArrMatchmatrix$

----) otherwise, add MK_i in $NoTopicmatrix$

Suppose out of 12 Main reference matrix 3 words are matched.

$$\boldsymbol{ArrMatchmatrix} = \begin{bmatrix} \boldsymbol{mk_1} \\ \boldsymbol{mk_4} \\ \boldsymbol{mk_6} \end{bmatrix} \tag{4.20}$$

$$\boldsymbol{NoTopicmatrix} = \begin{bmatrix} \boldsymbol{mk_2} \\ \boldsymbol{mk_3} \\ \boldsymbol{mk_5} \\ \boldsymbol{mk_7} \\ \boldsymbol{mk_8} \\ \boldsymbol{mk_9} \\ \boldsymbol{mk_{10}} \\ \boldsymbol{mk_{11}} \\ \boldsymbol{mk_{12}} \end{bmatrix} \tag{4.21}$$

As aforementioned in Eqn. 4.15, 4.16, 4.17 and 4.18, which indicates that each MK has their own respective SK.

Thus,

Matched MK is retrieved from $ArrMatchmatrix$ and retrieve their respective Co-Occurrence Reference Matrix from SK.

$$\boldsymbol{SK_{mk_1}} = \begin{bmatrix} \boldsymbol{mk_1} & \boldsymbol{sk_1} \\ \boldsymbol{mk_1} & . \\ \boldsymbol{mk_1} & \boldsymbol{sk_7} \end{bmatrix} \tag{4.22}$$

$$\boldsymbol{SK_{mk_4}} = \begin{bmatrix} \boldsymbol{mk_4} & \boldsymbol{sk_1} \\ \boldsymbol{mk_4} & . \\ \boldsymbol{mk_4} & \boldsymbol{sk_9} \end{bmatrix} \tag{4.23}$$

$$\boldsymbol{SK_{mk_6}} = \begin{bmatrix} \boldsymbol{mk_6} & \boldsymbol{sk_1} \\ \boldsymbol{mk_6} & . \\ \boldsymbol{mk_6} & \boldsymbol{sk_5} \end{bmatrix} \tag{4.24}$$

Now compare matrix X with Co-Occurrence reference matrix
i.e. compare $ArrMatchmatrix$ with X

----) if, there is match has then added SK_{mk_i} in $SubMatchmatrix$

----) otherwise, add SK_{mk_i}in $ArrResultmatrix$

Suppose matched Co-Occurrence Reference Matrix for Main Reference Matrix are as follows

$$\boldsymbol{SMK_{mk_1}} = \begin{bmatrix} \boldsymbol{mk_1} & \boldsymbol{sk_1} \\ \boldsymbol{mk_1} & \boldsymbol{sk_4} \\ \boldsymbol{mk_1} & \boldsymbol{sk_5} \\ & \boldsymbol{sk_7} \end{bmatrix} \qquad (4.26)$$

$$\boldsymbol{SMK_{mk_4}} = \begin{bmatrix} \boldsymbol{mk_4} & \boldsymbol{sk_1} \\ \boldsymbol{mk_4} & \boldsymbol{sk_4} \\ \boldsymbol{mk_4} & \boldsymbol{sk_5} \\ & \boldsymbol{sk_7} \\ & \boldsymbol{sk_8} \\ & \boldsymbol{sk_9} \end{bmatrix} \qquad (4.25)$$

$$\boldsymbol{SMK_{mk_6}} = \begin{bmatrix} \boldsymbol{mk_6} & \boldsymbol{sk_1} \\ \boldsymbol{mk_6} & \boldsymbol{sk_4} \\ \boldsymbol{mk_6} & \boldsymbol{sk_5} \end{bmatrix} \qquad (4.26)$$

$$\boldsymbol{SubMatchmatrix} = [\boldsymbol{SMK_{mk_1}}, \boldsymbol{SMK_{mk_4}}, \boldsymbol{SMK_{mk_6}}] \qquad (4.27)$$

Traverse both the $ArrMatchmatrix$ and $SubMatchmatrix$

$$\boldsymbol{Word\ Level\ reference\ Score} = \begin{cases} \boldsymbol{if\ Match,\ \ increment\ Counter\ by} = \mathbf{0.5} \\ \boldsymbol{else\ \ , Counter\ remain\ same} \end{cases} \qquad (4.28)$$

$$\boldsymbol{N - Gram\ Co - Occurrence\ reference\ Score} = \begin{cases} \boldsymbol{if\ Match,\ \ increment\ Counter\ by} = \mathbf{1} \\ \boldsymbol{else, Counter\ remain\ same} \end{cases} \qquad (4.29)$$

From Equation 30 and 31, the value of the counter computed below:

$Counter = ((3 * 0.5) + (13 * 1))$

$Counter = (1.5 + 13)$

$Counter = 14.5$

$$\boldsymbol{DOU} = \left\{ \frac{(\boldsymbol{Counter})}{\left(\frac{\boldsymbol{Number\ of\ rows\ in\ main\ reference\ matrix}}{\mathbf{2}}\right) + (\boldsymbol{Number\ of\ \ rows\ in\ Co{-}Occurrence\ matrix} * \mathbf{1})} * \mathbf{100} \right\} \qquad (4.30)$$

Let us consider the total number of Sub lexicon for 12 Main lexica are 40.

Then, from Eqn. 4.32, the degree of understanding is computed as follows:

$$Degree\ of\ Understanding = \left\{ \frac{14.5}{\left(\left(^{12}/_{2}\right) + (40)\right)} \right\} * 100$$

$$Degree\ of\ Understanding = \left\{ \frac{14.5}{(46)} \right\} * 100$$

$$Degree\ of\ Understanding = 31.52\ \%$$

4.2.4.2. Attainment Level

The attainment level of the learner is examined using the ‘Degree of Understanding’ Module. This is the subjective test, in which the learner is prompted to enter his/her understanding of the learning content, in the form of plain text. Further, their responses are analyzed to obtain scores and compute the degree of understandability (refer to Equation 4.30). This score indicates the percentage of learning grasped by the learner.

Summary

The design of the adaptation modules incorporated in the Pedagogy model, the Custom-Tailored Curriculum Sequencing Model, Tutoring Strategy Recommendation model, and Learner Performance Analyzer Module (psychological and non-psychological) have been discussed. Additionally, the composition of Pedagogy Style, the design of the Course coverage plan depending on prior knowledge, and the methodology of the selection of the Tutoring Strategy is presented. The Tutoring Strategy, architecture design offers personalized tutoring strategies for educating a specific topic to the learners.

The next chapter discusses the implementation of SeisTutor, and details its working with schematic and flow diagrams.

Chapter 5 Implementation of Prototype Intelligent Tutoring System-SeisTutor

This chapter introduces execution of SeisTutor, which includes sub-components of the Learner Model, Pedagogy Model, Domain Model, Expert Model, and Learner Interface Model. The Domain Model includes the Course Manager and the Knowledge Repository sub-components. The Pedagogy Model includes the Curriculum Identification Module, the Tutoring Strategy Recommendation Module, and the Learner Performance Analyzer Module sub-components. The interconnection, functioning and data flow is described in the chapter using the DFDs.

5.1 Implementation of the System

SeisTutor is coded by using the C# .NET framework. Data is stored through the MS Access database running on Windows platform. CNN based Emotion Recognition Module is implemented using Python, which is integrated into the SeisTutor C# code. This is a standalone offline application compatible to Windows platform.

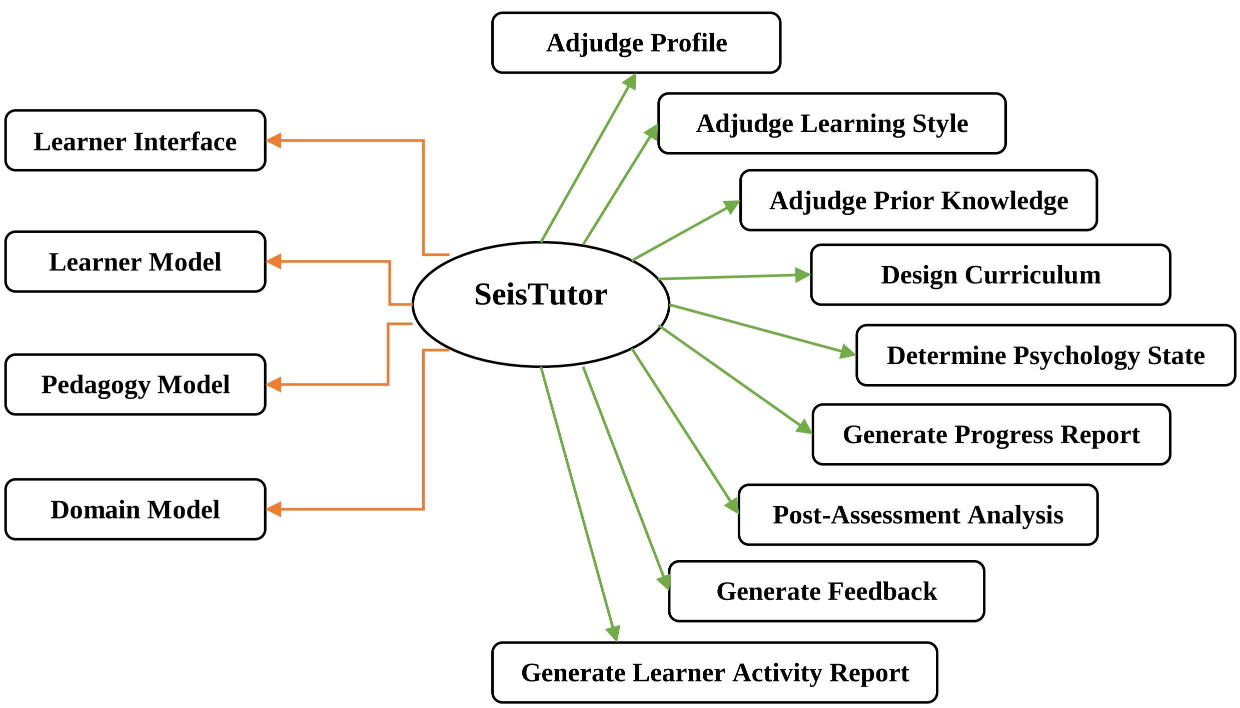


Figure 5-1 Level 0 - DFD of SeisTutor

5.2 Learner Interface Model

The Learner Interface Model is a key component of an ITS because it provides a medium through which a communication is established between the learner and the system. It aids the learner in learning and ITS, for offering learning material during learning sessions. This model is not only to facilitate the learner to visualize their results but also provides a personalized interaction mode of learning. It plays a significant role in ITS, as it enables the learner to access the system functionalities. Figure 5.2 presents the main window of the learner interface model.

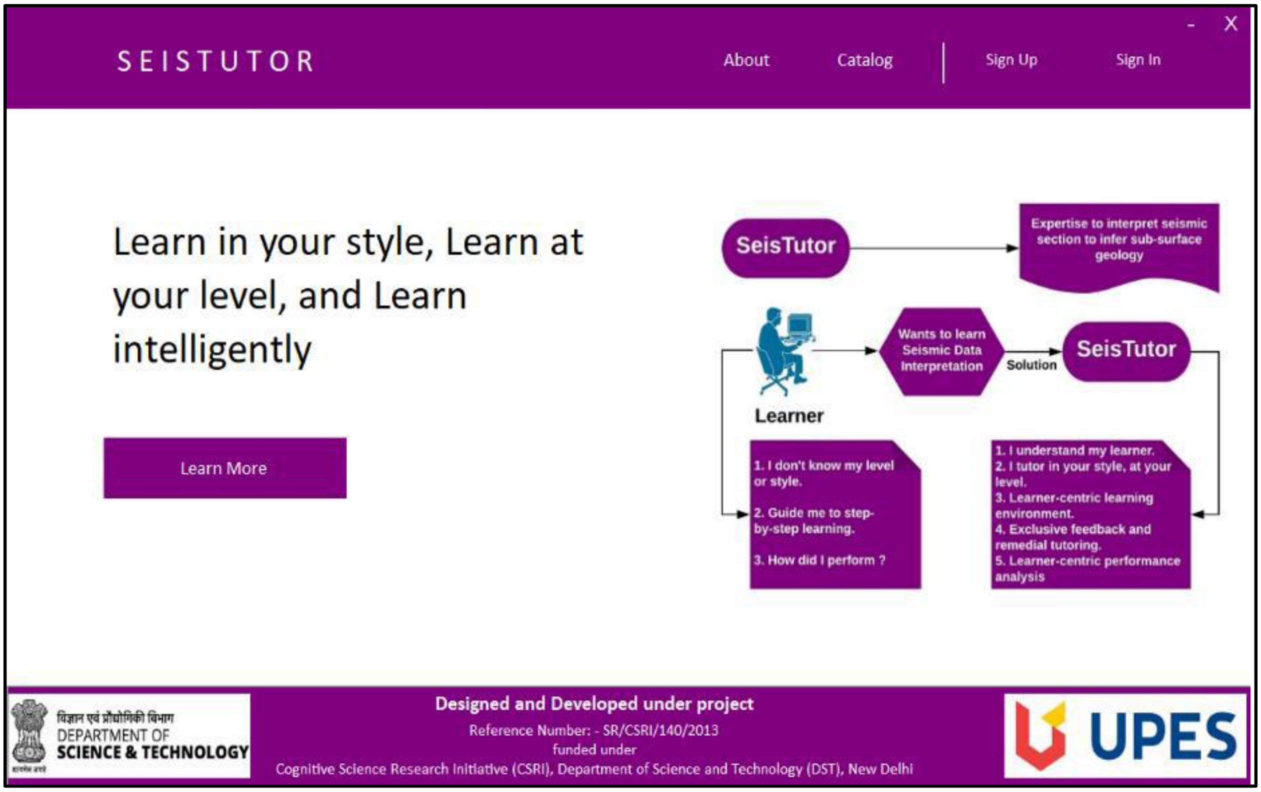


Figure 5-2 Main Window of the Learner Interface

In addition to this, the learner interface is used to visualize the learning material by means of rich intrinsic multimedia artifacts like pictures/images, audio, and video. By establishing interaction with the other models, this model can offer learning material, assessment materials, hints, feedback, and learning progress statistics to the learner.

5.2.1 Learner Registration

Learner Registration sub-component enables the learner to register with the tutoring system. For registration, three credentials are required, a unique username, email-id, and password. If the username is unique, then the system saves learner credentials and generates a unique learner id. Furthermore, this unique learner id is used to manage the learning sessions, gauge the learner activities, facilitating in making the strategic decisions.

Fig. 5.3 and 5.4 illustrates the learner registration process flow and learner registration interface, respectively.

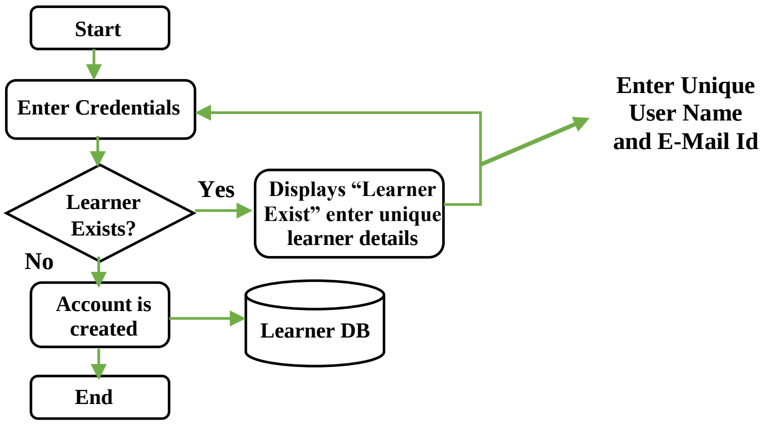


Figure 5-3 Process of Registering with SeisTutor

Figure 5.3 demonstrates the system which is accepting the details of the learner for the first time, if the learner is existing learner then the system presents notification to enter unique credentials (User Name and Password).

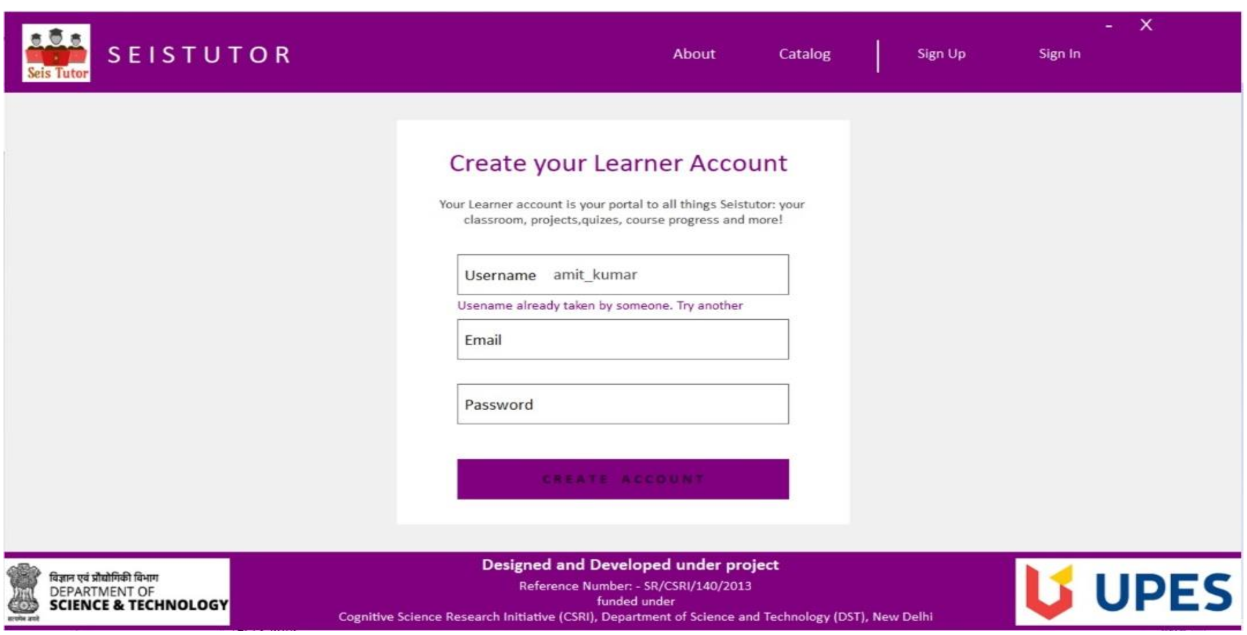


Figure 5-4 Learner Registration Interface

Following security features are built in while creating a new user account. For creating the learner account, the learner has to enter the valid length of user name (min 6 character), email id will be an authentic email id i.e. it should contain one @ followed by the dot symbol, and password will be in the combination of at least 2 numeric, 1 special character and 1 Capital letter.

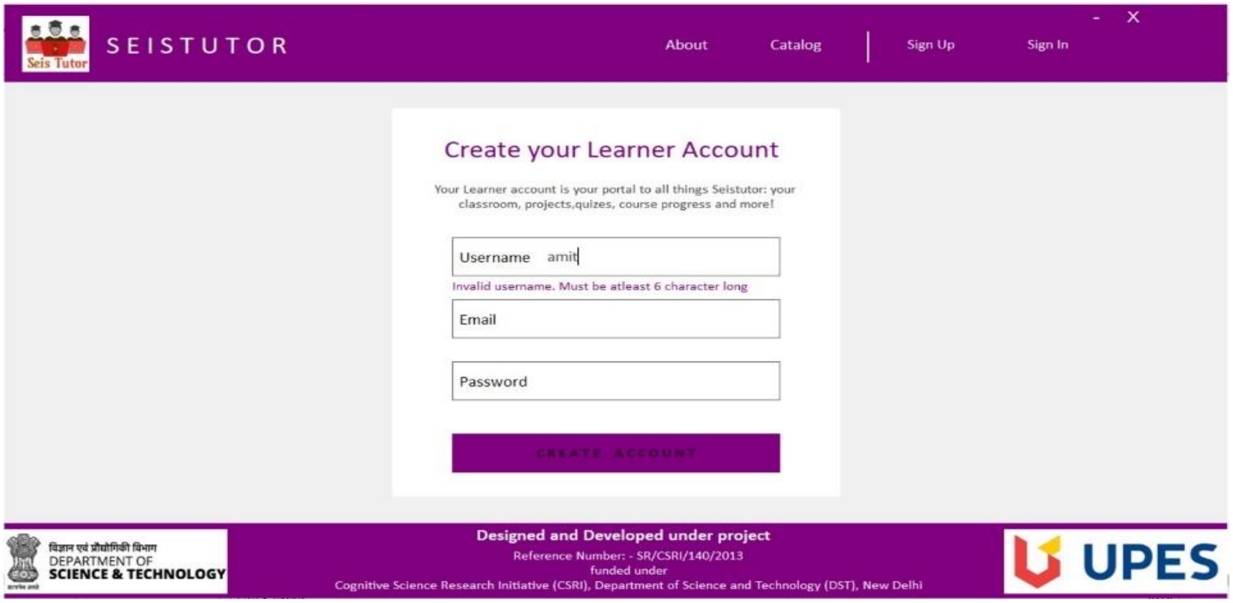


Figure 5-5 User Name validation interface

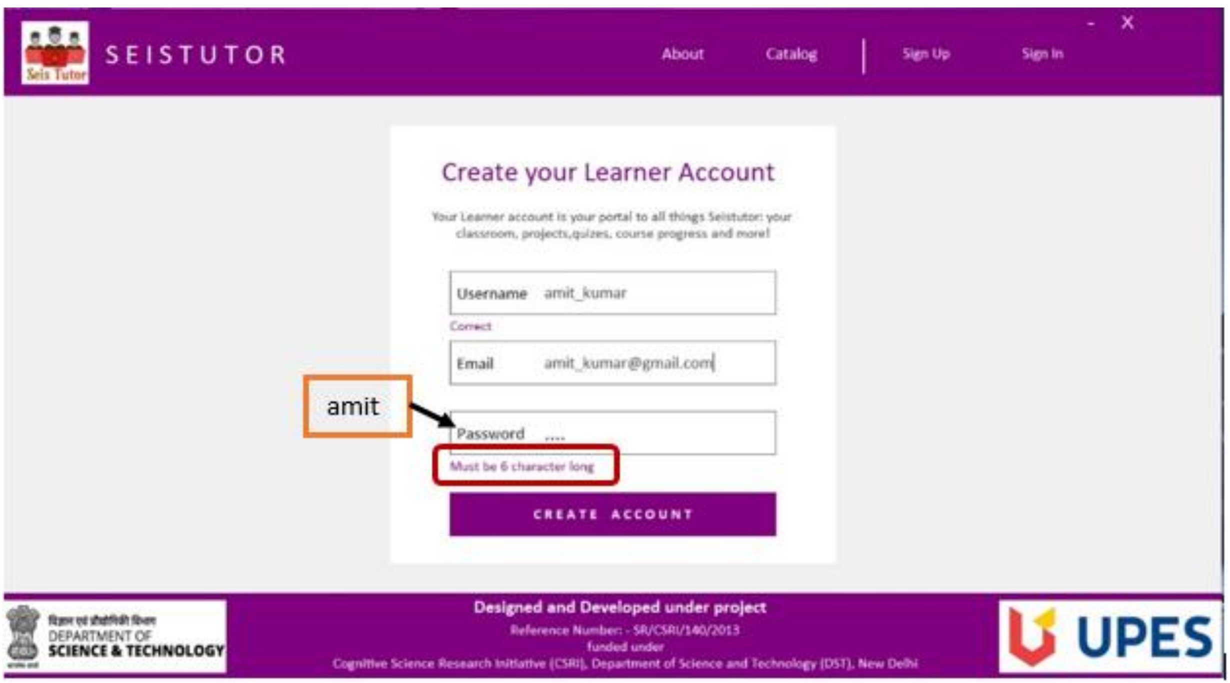


Figure 5-6 Password character length validation interface

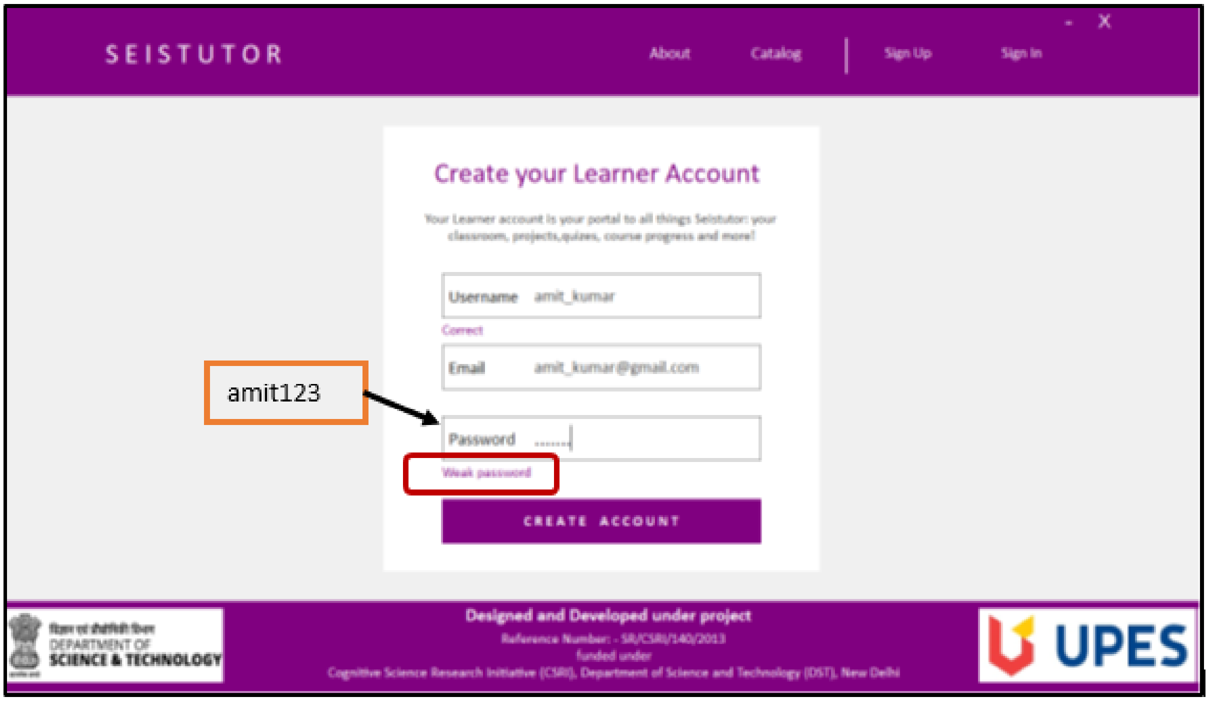


Figure 5-7 Weak password validation interface

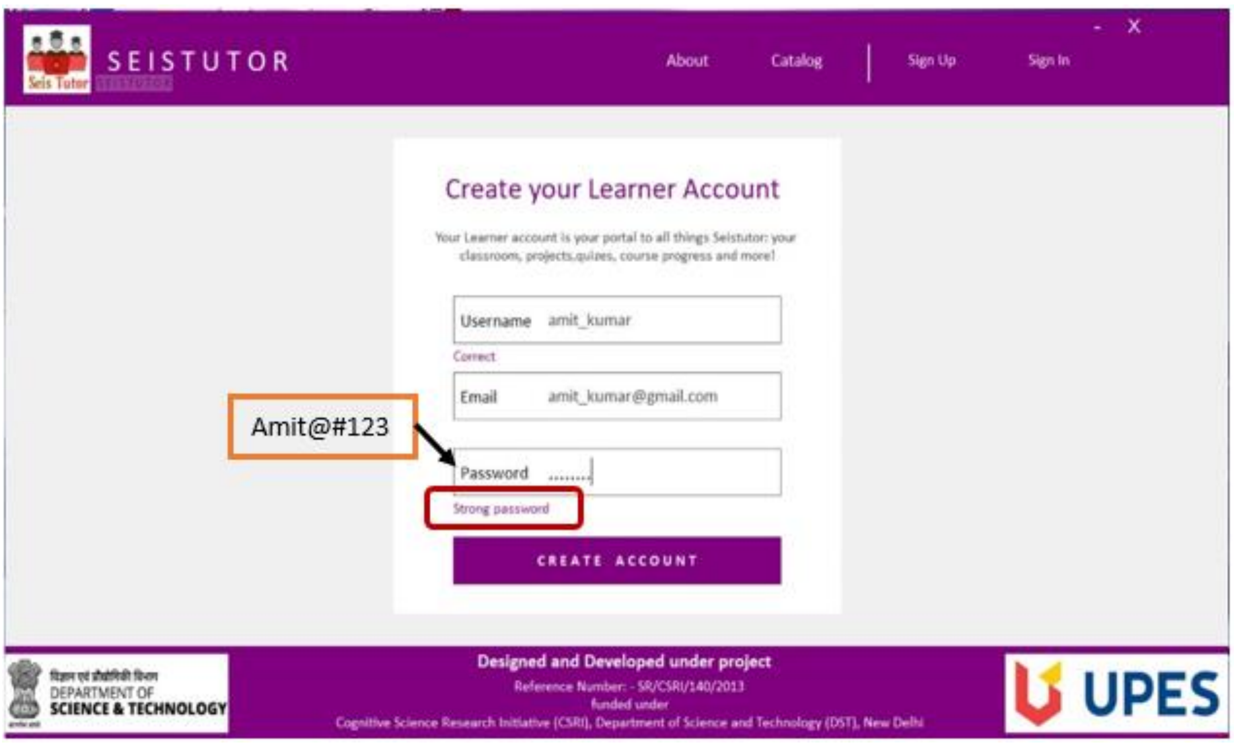


Figure 5-8 Strong password validation interface

5.3 Domain Model

The domain model comprises the knowledge base of the SeisTutor. It organizes the structure of the course to be delivered (topic/sub-topics, and the association between the topics). The domain model represents the *'What-to-teach'* component of the SeisTutor. Fig. 5.9 shows the DFD of the domain model.

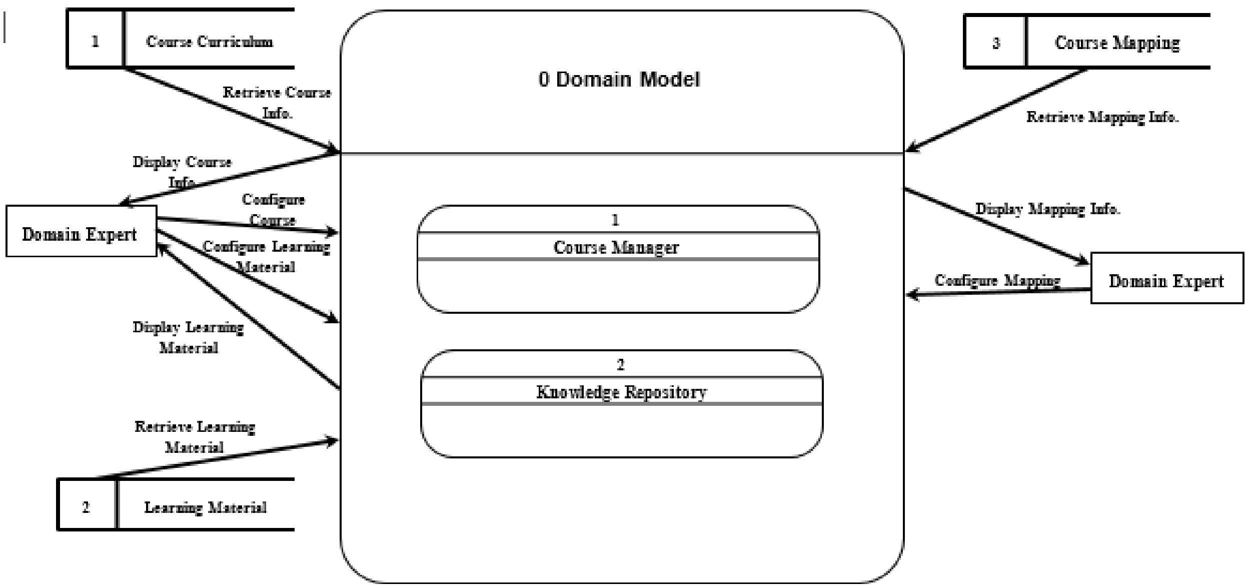


Figure 5-9 DFD of the Domain Model

The domain model consists of two sub-components, the first is the Course Manager, which contains the structure of the domain and organizes the course in the manner easy to understand and the other is the Knowledge Repository which stores the learning and test material in the database. The learning content is represented by the meta-description attributes. The meta-description forms of learning content help the system to reuse and track the learning content from the knowledge base of the SeisTutor. The experts perform the course mapping task through the expert interface module. Fig. 5.10 presents the working of Domain Model and Fig. 5.11 presents the domain model interface. As shown in Fig. 5.10, Pedagogy Model makes retrieval request to Domain Model, for retrieving learning content based upon the Tutoring Strategy. The Course Manager of Domain Model retrieves learning material from the knowledge Repository. Learning Materials in the Knowledge Repository are organized in the form of Knowledge Capsules. As there are twelve Tutoring Strategy hence, Knowledge Repository comprises of twelve Knowledge Capsules. On receiving Learning Content from the Knowledge Repository, Course Manager organizes the Learning Material as per the recommended curriculum and hand over the material to the Pedagogy model for further processing.

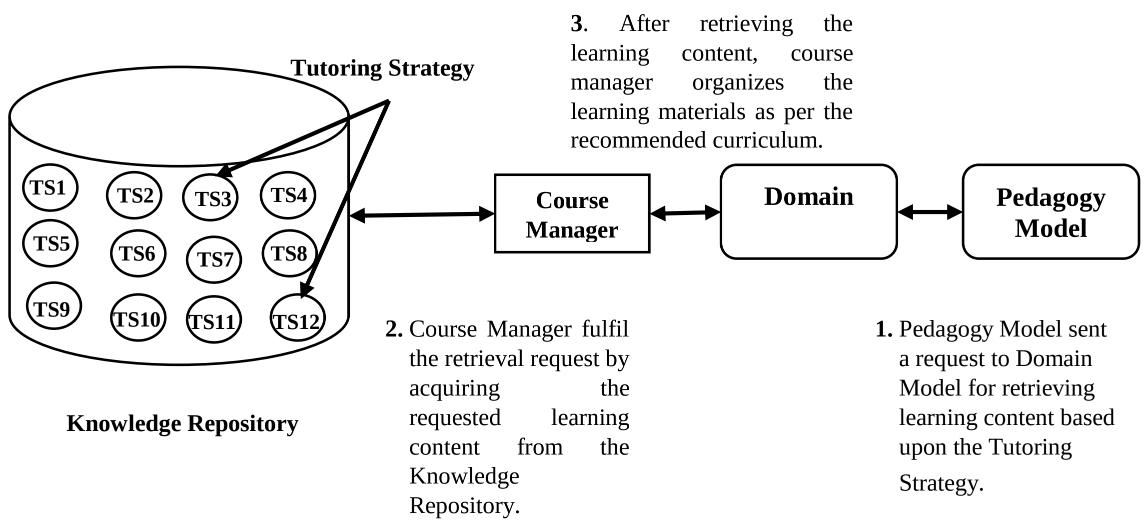


Figure 5-10 Step-Wise Execution of working of Domain Model.

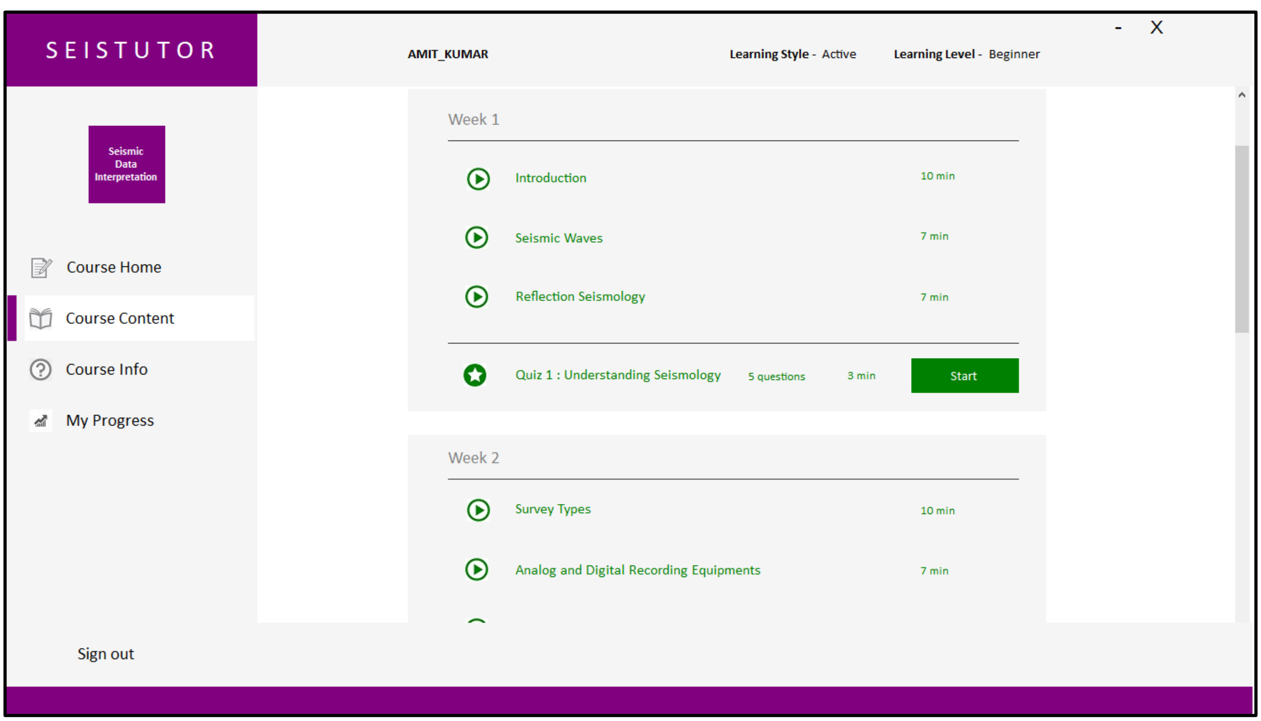


Figure 5-11 Domain Model Interface

5.4 Learner Model

The learner model is one of the critical components of SeisTutor. It stores the learner characteristics information such as Learner Profile, Learning Style, Prior Knowledge and Cognitive Skills. SeisTutor aims to provide a personalized learning environment. To accomplish this, SeisTutor incorporates cognitive intelligence. Learner Characteristics (Learner Profile, Prior Knowledge and Learning Style) play a vital role in generating appropriate pedagogy styles, which further improves the learner performances in many ways. Learning material as per the preferred style of learning makes the learning more comfortable, effective, and adaptable (Tseng, Chu, Hwang, & Tsai, 2008).

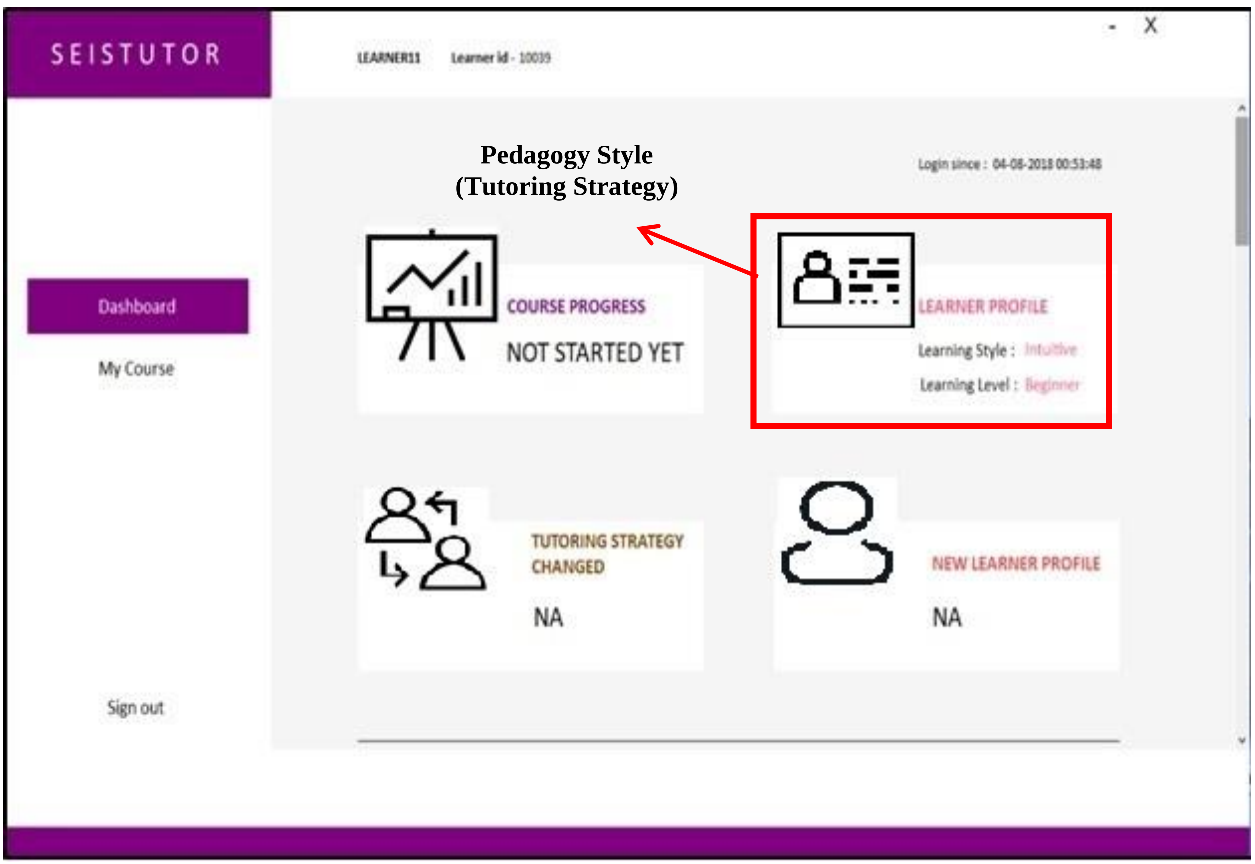


Figure 5-12 The Learner Model Interface (Home Page)

The learner characteristics model holds learner characteristics, such as domain Prior knowledge, Learning Style, and Learning Level. The learner characteristics help the system to determine the profile (*Beginner*, *Intermediate*, or *Expert*) of a learner. The screenshot of the learner model interface is presented in Fig. 5.12.

5.5 Pedagogy Model

The pedagogy model is the brain of an ITS as it is used to make fruitful decisions to mimic the human cognitive intelligence. The learner characteristics and the prior learner knowledge play a crucial role in incorporating adaptation/cognitive features in SeisTutor. As aforementioned, that learner characteristics information is gathered through two tests. The objective of the Domain Knowledge Test is to determine not only the learner profile, but also identify the learner's prior knowledge (See Fig. 5.13).

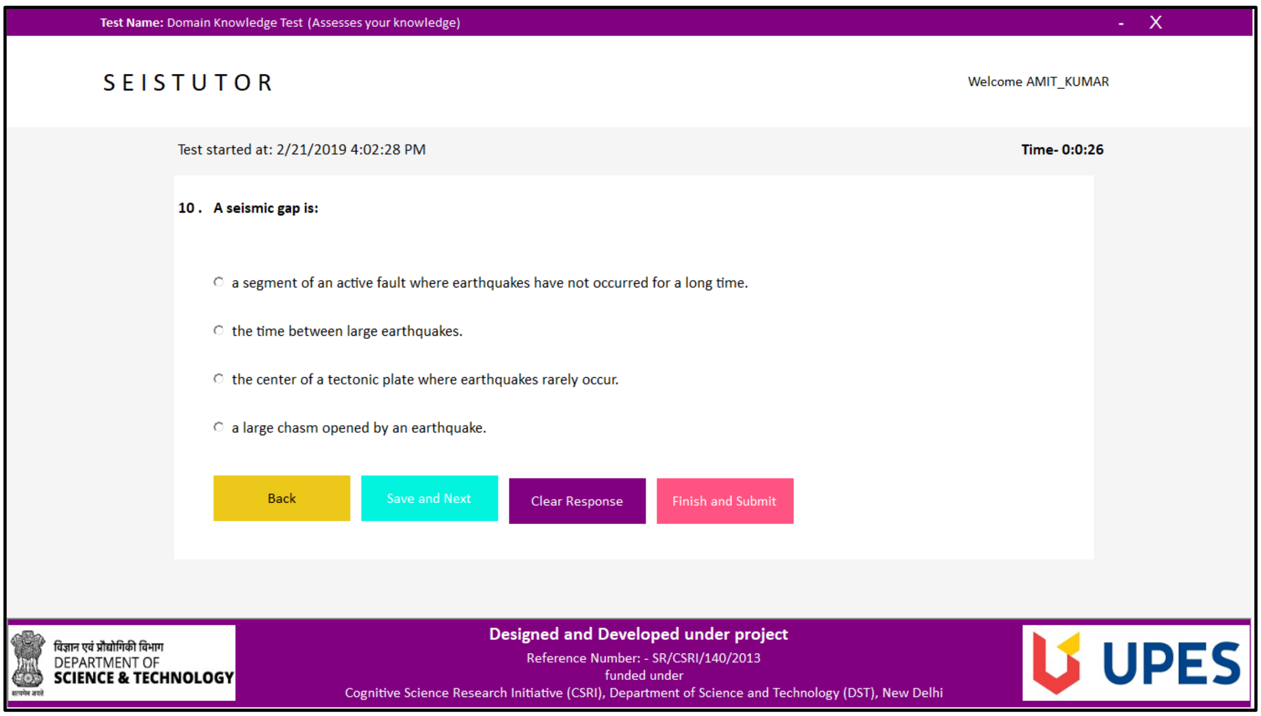


Figure 5-13 Domain Knowledge Test Model Interface

Learner Prior Knowledge indicates the acceptable threshold knowledge that the learner is already having on subject topics/sub-topics. Furthermore, it aids the SeisTutor in determining the list of topics on which learners have to put more emphasis on, and the same are realigned to form a Custom-Tailored Curriculum for the learner. The amalgamation of the designed curriculum and the Pedagogy Style, form an exclusive tutoring strategy. This personalized tutoring strategy is exclusively designed for the learner, which further improves the learner's performance in many ways. SeisTutor not only offers sequenced learning material aligned as per the learner grasping and preferred mode of learning, but also exclusively focuses on the subject topics/sub-topics where the learner is having less understanding. The screenshot of the Custom-Tailored Curriculum offered to the learner dashboard is shown in Fig. 5.15. Fig. 5.14 presents the DFD for the Pedagogy model and its subcomponents.

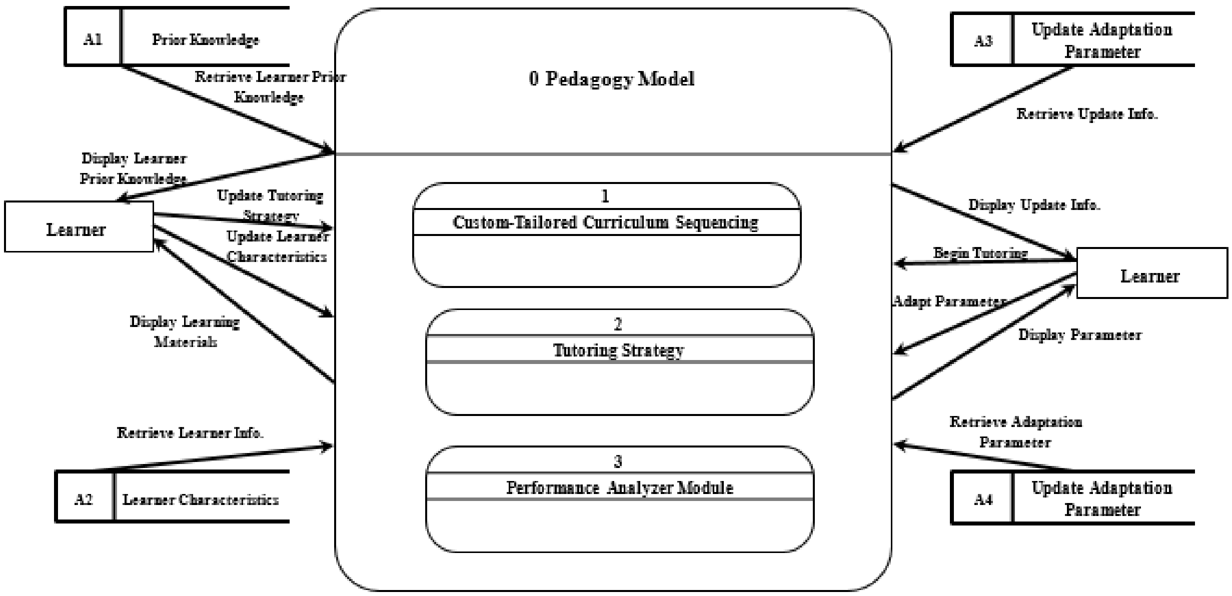


Figure 5-14 DFD of the Pedagogy Model

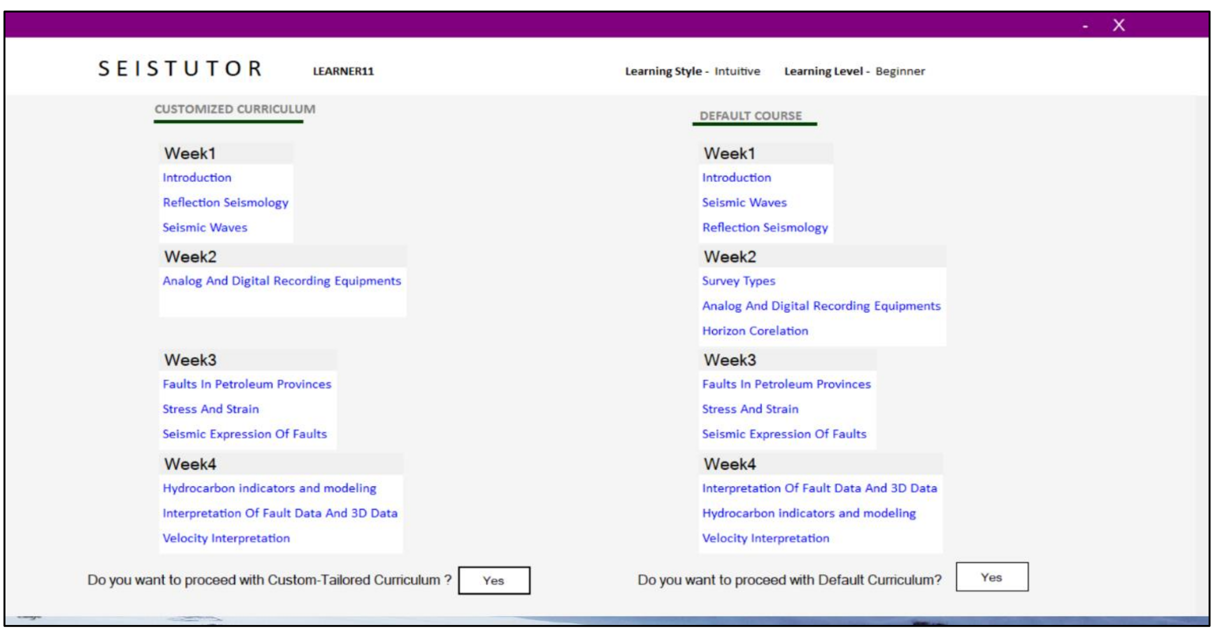


Figure 5-15 Custom-Tailored Curriculum offered to the learner.

In addition to this, pedagogy model is also responsible for determining the learner's emotions during ongoing learning sessions. Emotion recognition during an ongoing learning session play a vital role in establishing individuality feature. Here individuality indicates the individual psychological perceptions. This feature helps the learning systems in determining the learner understanding and overall satisfaction level. Therefore, emotion recognition feature embellish effective learning sessions and make the learning session worthwhile.

The Emotion recognition module has been implemented using Machine Learning Techniques of Artificial Intelligence. This module accepts input, an individual learner's snap during ongoing learning session and recognizes the psychological states (*"Happy", "Sad", "angry", "surprise", "fear", "disgust", "normal")*. Then these are displayed along with the learner progress. The whole process of gathering psychological (emotion) state is repeated until the learner completes all the learning content (topics) associated with all the weeks. Currently, the recognized psychological states are being used for the purpose of keeping track of learner emotions during the ongoing tutoring. The purpose of this module is to identify the learner's emotions towards the learning content offered by the SeisTutor and also identify their perceptions while exploring and learning (overall experience) through SeisTutor. Fig. 5.16 shows the working of emotion recognition module and Fig. 5.17 shows the emotion recognition during ongoing tutoring session.

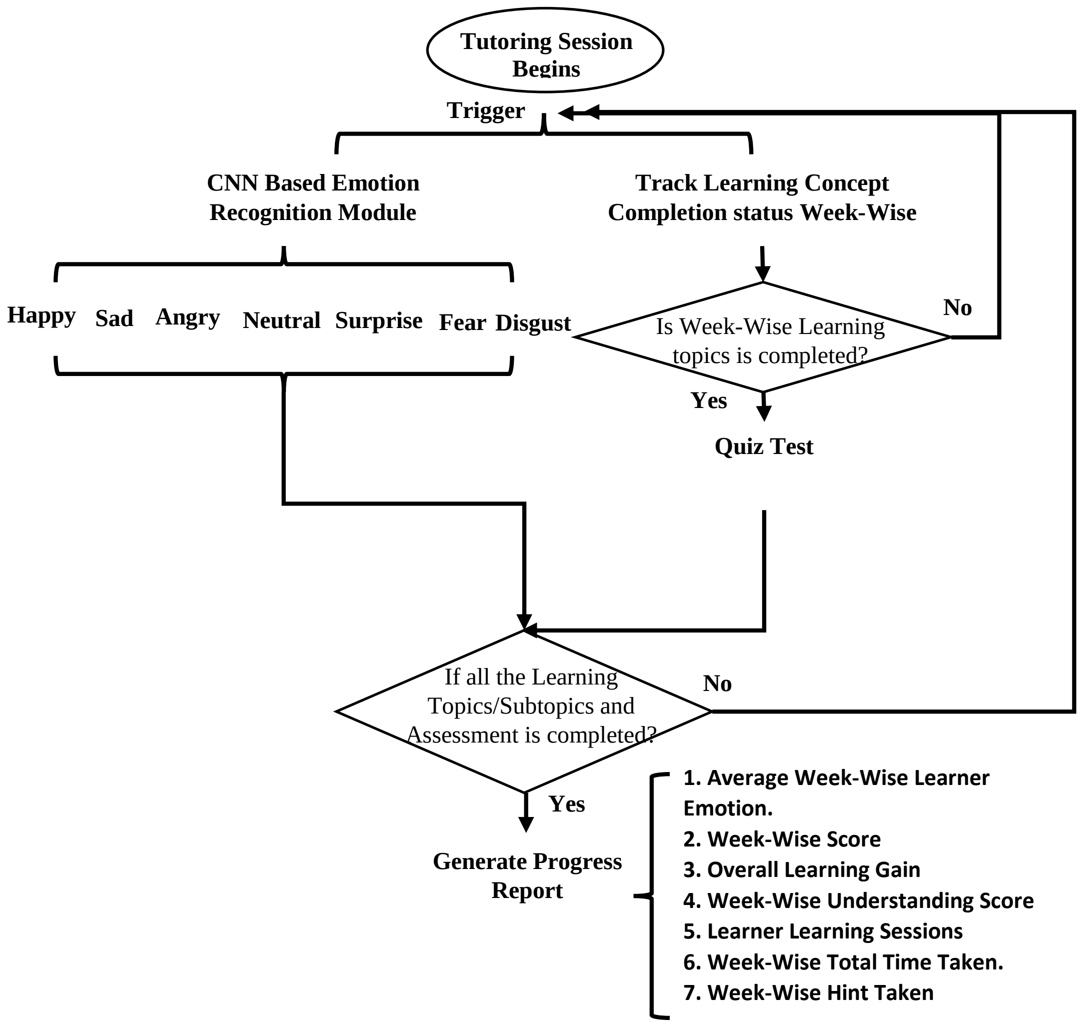


Figure 5-16 Working of Emotion Recognition Module during Tutoring Session

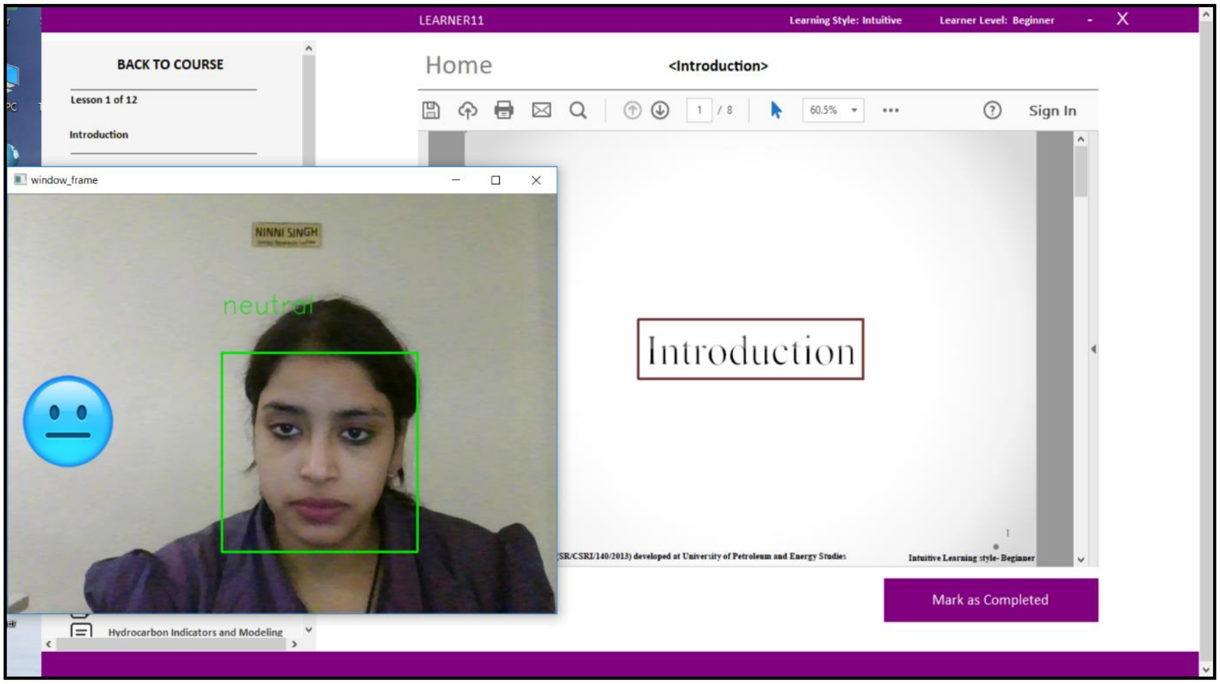


Figure 5-17 Emotion Recognition during the tutoring session

5.5.1 Performance Analyzer Module

The purpose of the Performance Analyzer module is to identify the degree of understanding of learning content. The degree of understanding is the subjective test, it is executed in a week-wise pattern. In this test learner is prompted to enter his/her understanding of the learning content, in the form of plain text. The learner is expected to make use of maximum keywords related to the learning content of the given topics/ chapters/sub-topics of the week. The degree of understanding of the lesson is assessed through pattern matching of these keywords with the complete content of that topic/chapter/subtopic. The degree of understanding formulae is used to quantify the scores and compute the degree of understanding. Fig. 5.18 shows the understanding test for a computing degree of understanding.

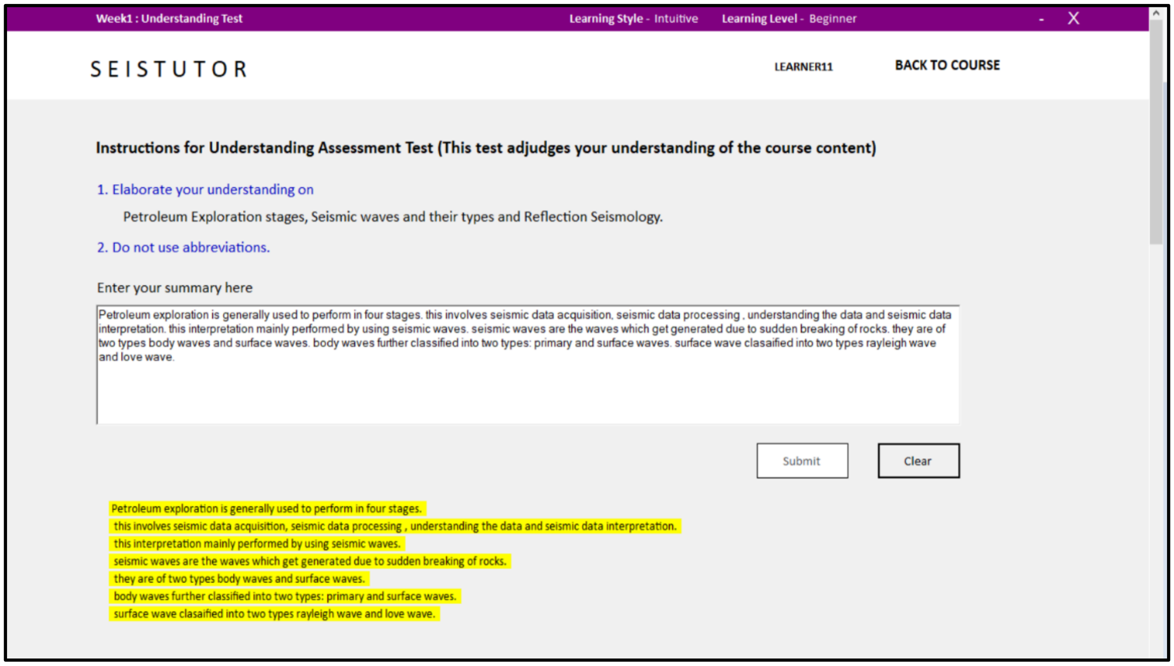


Figure 5-18 Understanding test for adjudging the learner degree of understanding

5.6 Learner Statistics

The tutoring system maintains two types of data. First, the Demographic data that provide necessary information of the learner, such as name, email id, age, highest qualification, occupation, etc. and second, is the personalized learning data that is generated during tutoring session which is further used by the system for decision making. The system records the learner activity during tutoring, and also makes use of the personalized data for assessing and evaluating the learner performance such as learner week-wise quiz performance, week-wise maximum occurrence emotions (emotion which was found to be for a maximum period of time during tutoring session), week-wise degree of understanding of learned concepts, login sessions, time spends on topics, Learning Gain and Dynamic Profile (Profile Shift (before and after learning)). These learner performances are shown with the help of visualization techniques, i.e. pie charts, line diagram and Bar graph. Fig. 5.19 presents the learner progress report generated by the SeisTutor.

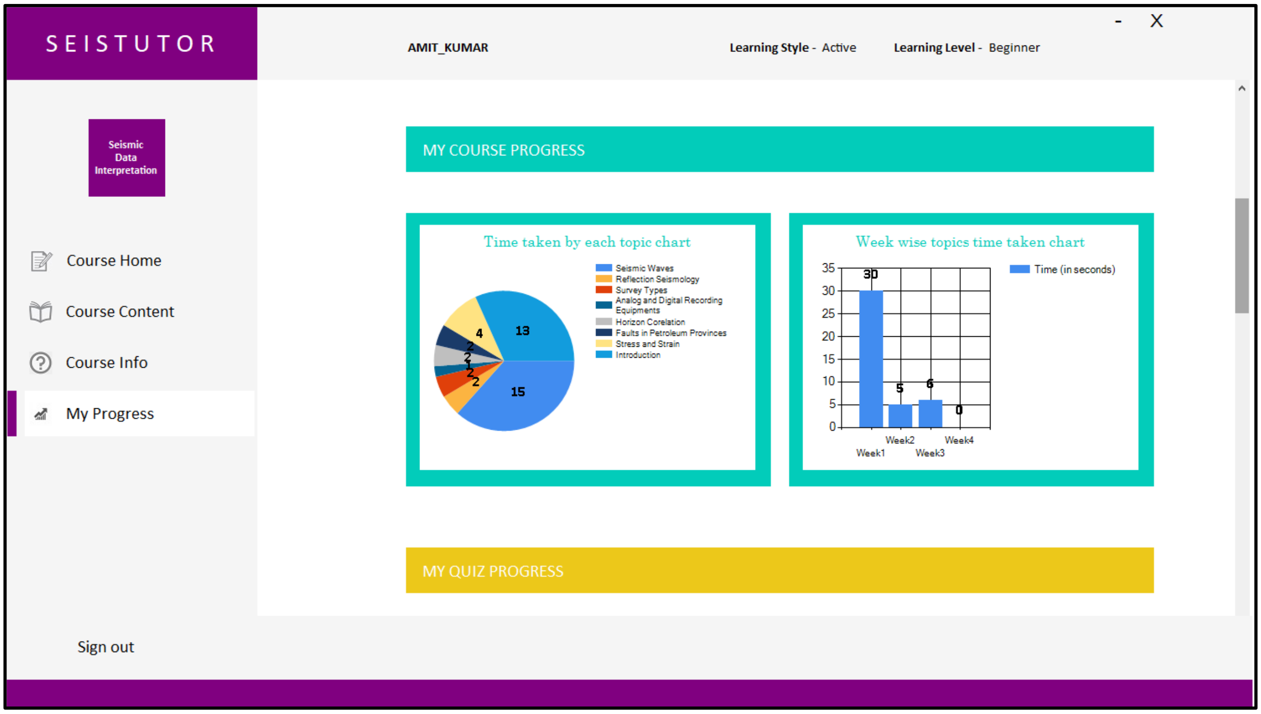


Figure 5-19 Learning Data Chart Stored with SeisTutor

5.7 Learner Feedback

The purpose of gathering learner’s feedback is to determine the learner's experiences, their perception, and provide suggestions for improvement. After completing the learning session, the learner has to give their valuable views. A pool of 44 question questionnaire was created, covering all aspects of SeisTutor such as adaptation features (Custom-Tailored Curriculum, Tutoring Strategy recommendation, emotion recognition and degree of understanding), ongoing support, personalization feature, etc. Appendix 2 presents the learner feedback report. Learner’s feedback plays a vital role in evaluating the effectiveness of the learning process, overall satisfaction level, learner adaptation and intelligence feature (CTCSS) incorporated in SeisTutor. The Learner feedbacks are ranked under five categories, i.e. strongly satisfied, satisfied, neutral, dissatisfied and strongly dissatisfied.

Neutral indicates that the learner is not able to strongly mark their experience with the system. Strongly dis-satisfied and dissatisfied indicates that the learner is not happy with the features experienced during the learning session. Strongly satisfied and satisfied indicates that the learner is happy with the features experienced during the learning session. Learner’s feedbacks provide on 5 points Likert scale 1-5.

Summary

This chapter deliberates the execution of Learner Model, Pedagogy Model and Domain Model, Learner Statistics and Learner Feedbacks components of the SeisTutor. The Learner Model is developed using fuzzy inference technique. It gauged the learner characteristics and recommend the initial Pedagogy Styles (Tutoring Strategy). The intelligence features of the Pedagogy model are implemented using the 'BUG' model (Custom-Tailored Curriculum Sequencing Module), Machine Learning Technique (CNN based Emotion Recognition Module), and word-based summary analyzer technique (Performance Analyzer Module). The bug model identifies the learner's previous/prior knowledge by identifying the bugs during the pretest (domain knowledge test) and further recommends the Learner-Centric learning path. A machine learning technique is used to implement the emotion recognition module. A CNN based Emotion Recognition Module tracks the learner's emotions during ongoing learning sessions. A word based summary analyzer technique enables the learners to summarize and write their understanding, based on the summary their understanding score is quantified. The DFD and screenshots of various components of the SeisTutor are shown.

In the following chapter, the statistical methods used for the evaluation of SeisTutor will be discussed.

Chapter 6 Evaluation of SeisTutor

This chapter describes the evaluation of the SeisTutor. This section describes the statistical methods and their application on the learner's performance parameters, captured during ongoing tutoring through SeisTutor.

6.1 Overview

This section describes the statistical methods used for evaluating the SeisTutor. Evaluation of developed software SeisTutor is an important aspect of this research work. The objective of this research is to quantify the effectiveness of SeisTutor in providing Learner-Centric learning environment for learning Seismic Data Interpretation domain. Thus, to accomplish this, SeisTutor has been tested on selected population of students and teachers from an anonymous university. Total 60 learners volunteered in the evaluation process. The participants were divided into two groups: Control Group and Experimental Group.

Control Group Evaluation: The Control Group participants are given a standard curriculum in which learning topics and subtopics are arranged in the unaltered sequence. Therefore, all the learners follow the same learning path.

Experimental Group Evaluation: The Experimental Group participants are offered Custom-Tailored Curriculum , in which, learning content is realigned based on the learner responses during their domain knowledge test, conducted as part of pre-test. Additionally, during a learning session, psychological state (emotions) and degree of understanding are determined which are, further used for post analysis purpose.

The aspects of comparison of the both the groups are represented in the table (Table 6.1). The purpose to compare the results is to identify the differentiation in the learning experiences.

Table 6-1 Feature-wise comparison of SeisTutor performance with two groups

	Control Group	**Experiment Group**
Personalized Tutoring contents	Offer learning content (similar curriculum) based on Tutoring Strategy (Pedagogy Style) (See Fig 6.1).	Offer personalized learning content (different curriculum) based on Adaptive Tutoring Strategy (See Fig 6.2).
Psychological State tracking	The Emotional state of the learner is not capturing during the ongoing learning session.	Determine the Emotional State (emotion) of the learner during the ongoing learning session.
Degree of Understanding computation	Learner's understanding of the concept, not adjudged.	Quantify learner's understanding of the concept.

Both the experiments are executed and the results have been monitored. Fig. 6.3 illustrates the flow of the evaluation process.

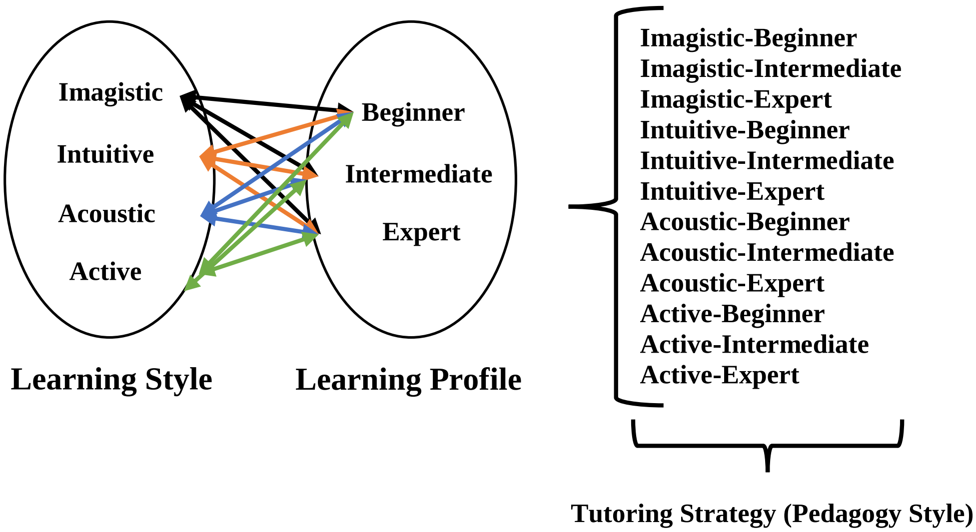


Figure 6-1 Tutoring Strategy (Pedagogy Style) Generation

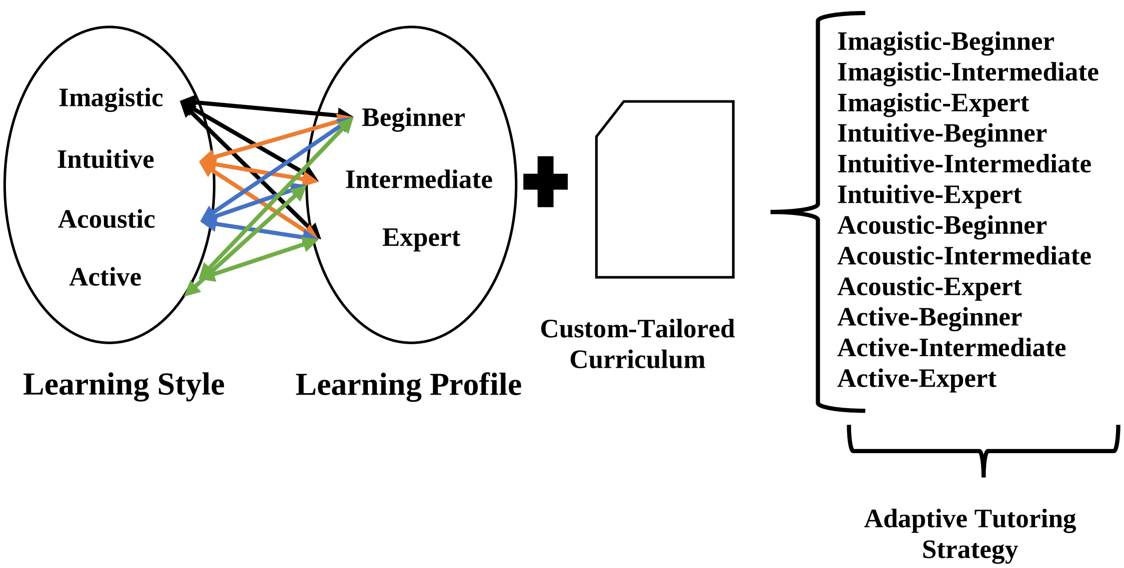


Figure 6-2 Adaptive Tutoring Strategy Generation Steps

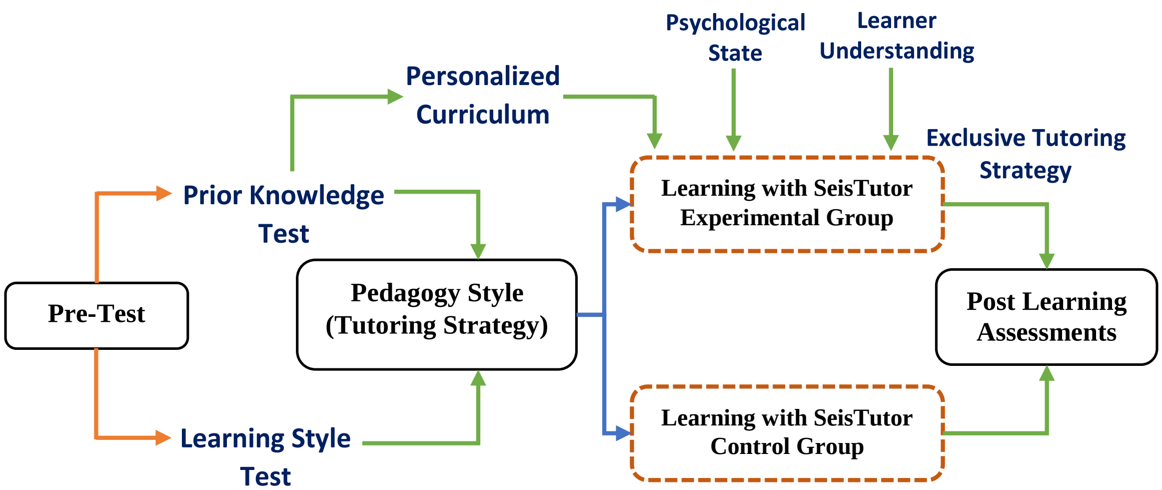


Figure 6-3 Flow of accomplishing the evaluation process.

To determine, their willingness to participate in the evaluation process, a consent form presenting, essential details of the process, was circulated amongst volunteers. Each participant must give their consent for participation in the evaluation process. Out of 60 volunteers, 32 of them were designated as Control Group and the remainder 28 designated as the Experimental Group. In the further text, these volunteers, will be referred to as participants or learners. Table 6.2 presents the demographic profile of the participants.

Table 6-2 Demographic Characteristics of participating Learners

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 %

During the ongoing session, SeisTutor captures the learner's pretest scores, quiz scores, emotions, degree of understanding test scores and their feedback. These are captured separately for control and experimental groups. These parameters are normalized first for further processing. There are two aspects of the evaluation, first aspect, is to identify which group presents an improvement in learner's learning/aptitudes (i.e. test results) and the second aspect is to determine the learner's reactions, comfort level, behavior and overall results. The first aspects of evaluation are accomplished by using one Tailed ANOVA statistical test. The Analysis of Variance (ANOVA) statistical test is used and considered an appropriate test for judging the significance of the sample means or for judging the significant differences between the two samples (i.e. pretest and the posttest) for both the groups. The ANOVA test is utilized to compare two populations or samples in which you have two examples of observations which matched together (e.g. learner test results before and after a specific course, i.e. Pretest, Posttest). The relevant test statistics of F-ratio is calculated from the sample data and then compared with the value based on F-distribution (read from the F-table for the different level of significance of the different degree of freedom).

Two estimations of sample variance take into consideration, one based on between samples variance and the other based on within sample variance. Then both the estimations of sample variance are compared with an F-ratio (see Fig. 6.4).

$$F = \frac{Estimate\ of\ population\ variance\ based\ on\ between\ samples\ variance}{estimate\ of\ population\ variance\ based\ on\ within\ samples\ variance}$$

The second aspect of evaluation is accomplished by utilizing Kirkpatrick four phase Evaluation Model. Kirkpatrick evaluation prototype comprises of four-phases shown in Fig. 6.5 and Fig. 6.6. Fig. 6.7 shows the Statistical evaluation technique which is used for demonstrating the evaluation of SeisTutor by employing Kirkpatrick four phase evaluation model.

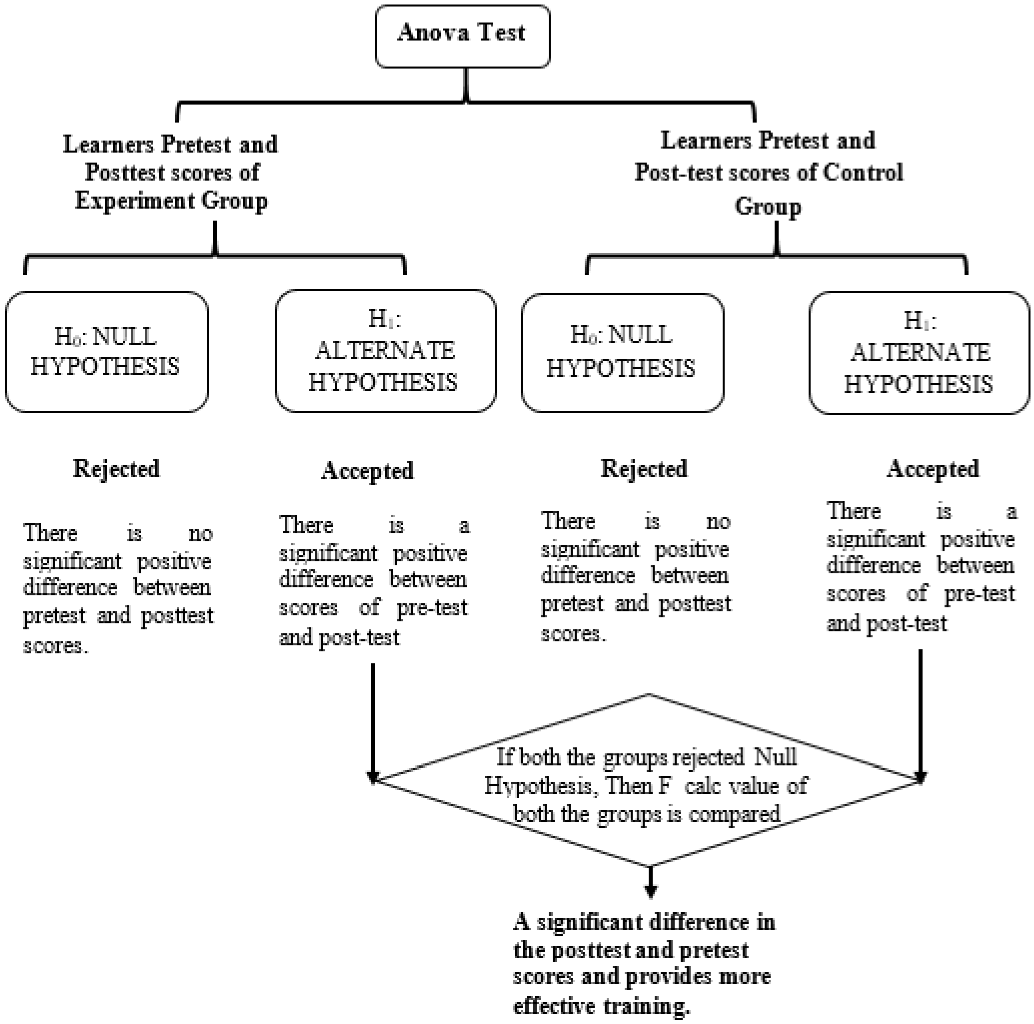


Figure 6-4 Rules of Deduction of ANOVA Test

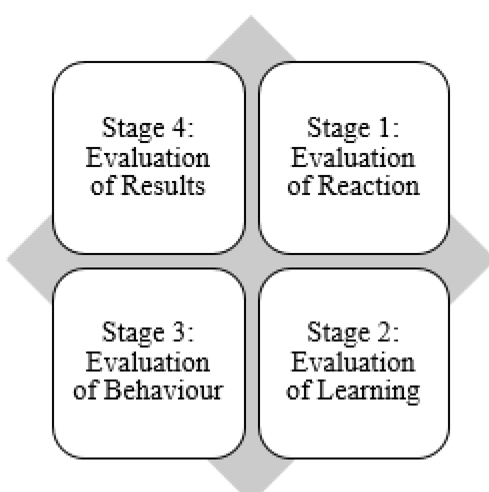


Figure 6-5 Kirkpatrick's four-stage evaluation

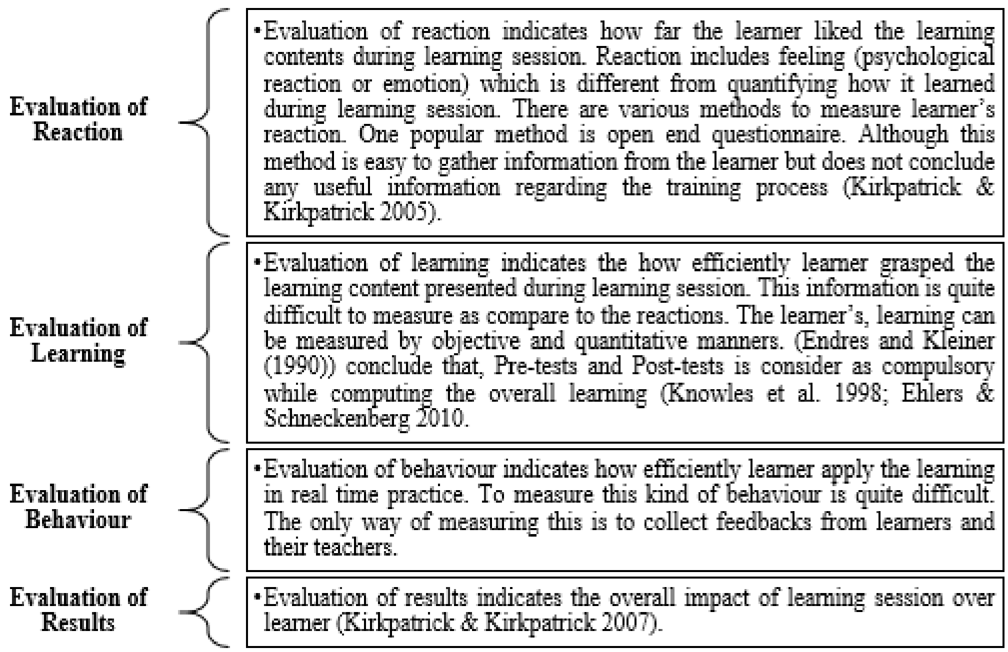


Figure 6-6 Brief illustrations of Kirkpatrick's four-stage of evaluation.

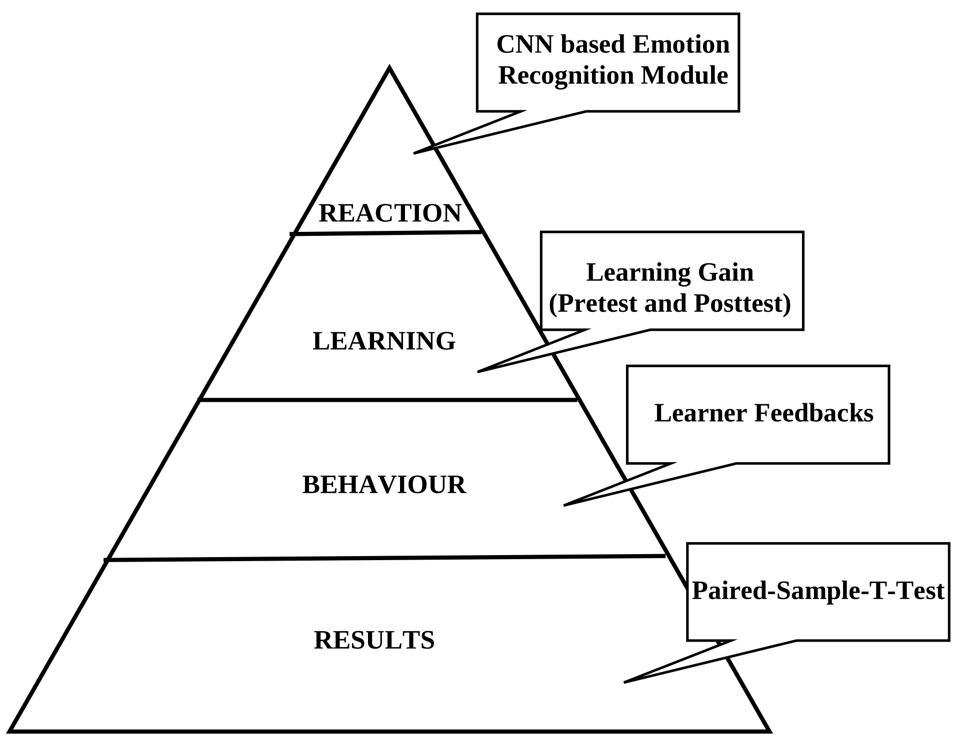


Figure 6-7 Statistical evaluation technique which is used for demonstrating the evaluation of SeisTutor by employing Kirkpatrick four phase evaluation model.

In addition to this a comparative analysis is performed between the proposed ITS i.e. SeisTutor with the existing online Learning Systems. These learning systems are analyzed on seven parameters, i.e. (‘*GUI based*’, ’*Learner-Centric Learning Environment*’, *’Dynamic Profile*’, ’*Learning Content*’, ’*Resolving Learner Query during Session*’, *‘Navigation Support*’, and ’*Learner Feedback*’) .

6.2 Learner Statistics

As shown in Table 6.2, a higher percentage of the learner population (58 %) was male against female participants. The 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 the learners, belonging to subject domains such as Petroleum Engineering and Petroleum Exploration. The participants, included undergraduate learners (Under graduate program of Petroleum engineering), Teachers (Petroleum Engineering department) and others, mainly practitioners (from public sector undertaking company belonging to the exploration industry).

6.2.1. Data Preparation

The data obtained in the experiment, was screened, through elimination of missing values. Further normalization of data was performed using MIN-MAX Normalization. SPSS version 25 was used for the analysis.

6.2.2. Min Max Normalization

For evaluating the learner's performance, learner’s scores (Domain Knowledge Test, Post Assessment Test, and Learning Gain) are normalized 0 to 5 Likert Scale and psychological stats into 0 to 100. The Min-Max normalization transforms a value of X={x_1,x_2,x_3,………,x_n}, and fits in the range of [A, B]. The formula for Min-Max normalization is defined below, where

A is the lowest range; B is the highest range. In our case [A, B] is [0, 10];

$$\boldsymbol{Y} = \left\{\frac{x_i - \textit{Lowest value in } X}{\textit{Highest value in } X - \textit{Lowest value in } X}\right\} * (\boldsymbol{B} - \boldsymbol{A}) + \boldsymbol{A} \qquad (6.1)$$

6.2.3. Analysis of Learner Performance (First Aspects of Evaluation)

This section evaluates the learner's performance during the learning process. The Min-Max normalization techniques are used to normalize the performance parameters. Three performance parameters are used in this study: pretest score, week-wise quiz scores, and posttest score. The normalization performs a linear transformation of original scores and fits the score in the range of [0.0, 5.0]. Hence, data range, uniformity is maintained for further processing.

The score of learner performance of Week-1 Week-2, Week-3, and Week-4 is calculated and analyzed in both the groups. Pre Tutoring and Post Tutoring Performance

6.2.3.1. Pre Tutoring and Post Tutoring Performance

The participant's pretest (Pre-tutoring) and posttest performance are quantified and calculated for both the groups. The mean score pretest and posttest test for control and experimental groups are 2.41, 3.65, 1.72 and 3.94, respectively. The ANOVA test conducted on these scores.

H_0: Null Hypothesis: There is no significant positive difference between pretest and posttest scores, with the posttest score being higher, indicating that there is no improvement.

H_1: Alternate Hypothesis: There is a significant positive difference between scores of pre-test and post-test, with the post-test score being higher, indicating that there is an improvement.

6.2.4. Predictive Statistical Analysis of Degree of Understanding Module

This section evaluates the computational accuracy, recall and precision of Degree of Understanding module of the Performance Analyzer Module. As discussed earlier that after completion of every week, learners have to give quizzes and Degree of Understanding test. In this evaluation process, week-wise quiz score is considered as the control parameter while the Degree of the Understanding score is considered as the predictive parameter. As there are four weeks, and this predictive statistical analysis is performed on 28 learners (see Fig. 6.8). Thus, total number of observations are 112 (28 (learners) * 4 (4 weeks understanding test) = 112).

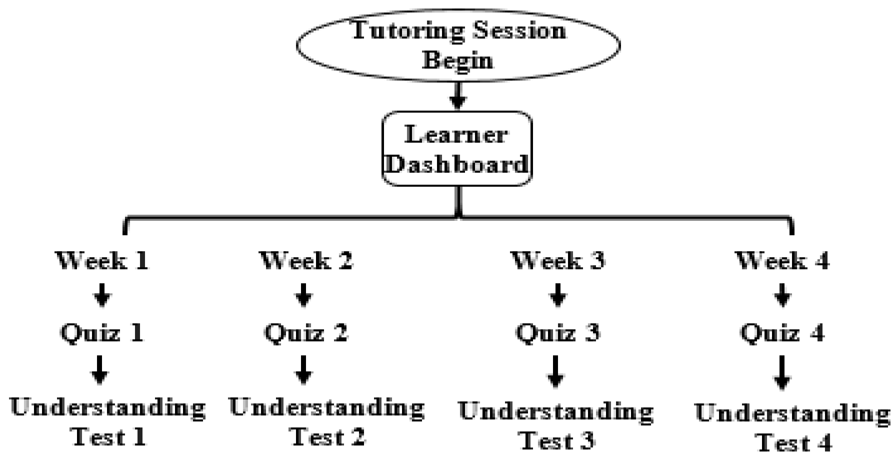


Figure 6-8 Flow diagram of Post Assessment Tests

6.2.4.1. Rubrics for Post Assessment Test.

Table 6-3 Performance Assessment Rubrics for Quiz Test.

Levels	Marks	Description
Level 0	0	Has no understanding of content.
Level 1	1	**Weak:** Struggling to understand the learning content.
Level 2	2	**Need Work:** Has little understanding of the material.
Level 3	3	**Good:** Has moderate understanding of the material.
Level 4	4	**Very Good:** Has very good or effective understanding of the material.
Level 5	5	**Excellent:** Has perfect or near-perfect understanding of the material.

Table 6-4 Performance Assessment Rubrics for Understanding Test.

Levels	Range	Description
Level 0	(0 %)	Has no understanding of content.
Level 1	(0 - 20 %)	**Weak:** Struggling to understand the learning content.
Level 2	(20- 40 %)	**Need Work:** Has little understanding of the material.
Level 3	(40 - 60 %)	**Good:** Has moderate understanding of the material.
Level 4	(60 - 80 %)	**Very Good:** Has very good or effective understanding of the material.
Level 5	(80 - 100 %)	**Excellent:** Has perfect or near-perfect understanding of the material.

6.2.5. Kirkpatrick Four Stage Evaluation (Second Aspects of Evaluation)

6.2.5.1.Kirkpatrick phase 1: Evaluation of Reaction:

In this phase learner reaction towards learning content and overall support provided by the learning system is determined. To determine learners reactions, SeisTutor incorporates the CNN based Emotion Recognition Module and open-end questionnaire (Learner Feedback). Therefore, in this evaluation, learner's emotions during ongoing learning sessions take into the consideration (participants of experimental group) (see Fig. 6.9).

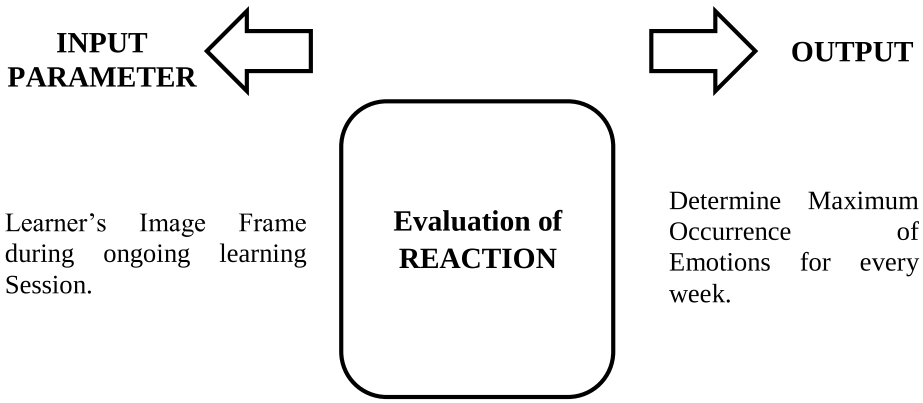


Figure 6-9 Input-Output Parameter for the evaluation of REACTION.

6.2.5.2.Kirkpatrick phase 2: Evaluation of Learning

In this phase learners overall learning is quantified. Therefore, learners quiz and Degree of Understanding test scores take into the consideration. In this phase learning gain for both the groups are quantified (quiz scores) and compared (see Fig. 6.10).

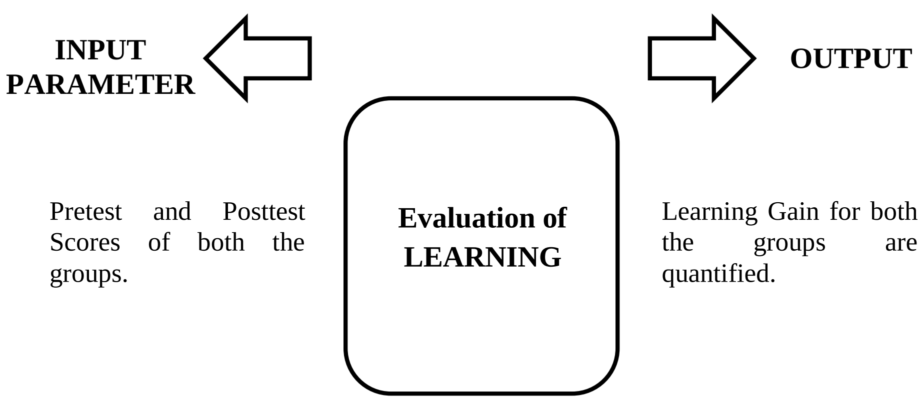


Figure 6-10 Input-Output Parameter for the evaluation of LEARNING.

Furthermore a correlation analysis, i.e. Bivariate Pearson Correlation is performed on these data. This correlation analysis determines the relationship between two parameters. The Hypothesis test for P value is.

H0: There is no significant relationship between Quiz Score and Degree of Understanding Score.

Ha: There is a statistically significant relationship between Quiz Score and Degree of Understanding Score.

Another reason of performing this correlation analysis is that this Degree of Understanding test is conducted only for the experimental group of learners. Therefore, the statistical comparative analysis based on the degree of understanding scores are not possible to perform. If this test rejects the H0: Null hypothesis, then there a linear relationship between learning gain and Degree of Understanding Score.

6.2.5.3.Kirkpatrick phase 3: Evaluation of Behaviour:

In this phase learner's behaviour towards, Effectiveness, Adaptation (incorporated artificial intelligence features), overall support, learner comfort level and Custom Tailored Curriculum Sequencing is quantified (see Fig. 6.11). Therefore, learner feedbacks are taken into the consideration. Learner feedbacks are taken on a five point Likert scale 0-5 (strongly satisfied, satisfied, neutral, dis-satisfied and strongly dis-satisfied).

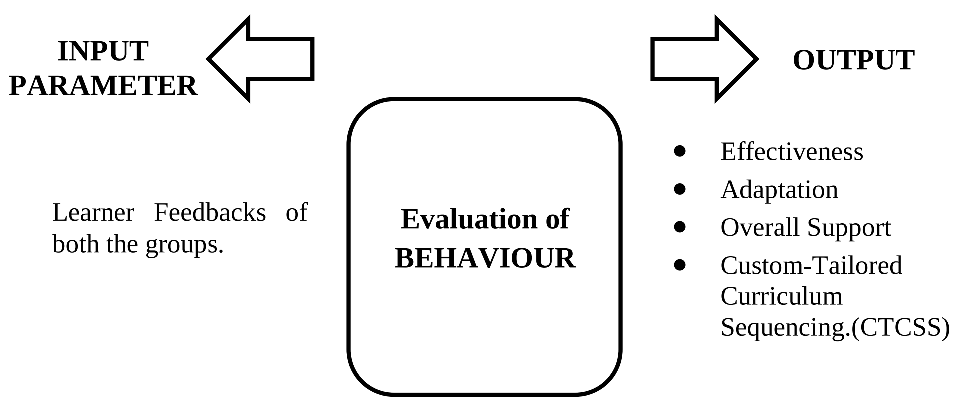


Figure 6-11 Input-Output Parameter for the evaluation of BEHAVIOUR.

6.2.5.4.Kirkpatrick phase 4: Evaluation of Results:

In this phase overall results in terms of effective learning are quantified. Therefore learner's pretest and posttest scores of participants involved in both the studies (Experimental and Control groups) take into the consideration. To quantify the effectiveness of learning, Paired Sample T-test is performed. Paired Sample T Test is the Robust T test, which determines the mean difference between the pretest and the posttest scores and determining whether it is zero or not. For effective learning there should be a large mean difference between pretest and posttest scores (see Fig. 6.12). Here two cases take into consideration.

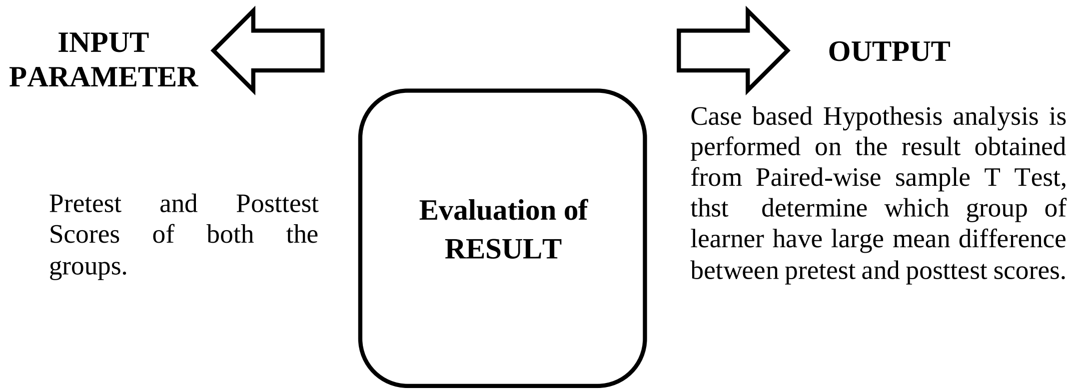


Figure 6-12 Input-Output Parameter for the evaluation of RESULT.

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

Hypothesis-Case-1.0: Let the participants involved in the Experimental group having similar pretest and posttest mean scores (negligible performance improvement).

Hypothesis-Case-1.1: Let the participants involved in the Experimental group having different pretest and posttest mean scores (effective performance improvement).

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

Hypothesis-Case-2.0: Let the participants involved in the control group having similar pretest and posttest mean scores (negligible performance improvement).

Hypothesis-Case-2.1: Let the participants involved in the control group having different pretest and posttest mean scores (effective performance improvement).

6.2.6. Comparative analysis of performance between the proposed Learner-Centric tutoring system "SeisTutor" with Existing online Tutoring Systems

6.2.6.1.MY-Moodle

My-Moodle is an open-source tutoring system, which helps the researcher to set up their learning environment (researcher are able to upload their learning materials and assessment tests) and test their proposed intelligent tutoring system. My-Moodle comprises of courses that contain resources and activities, i.e. glossaries, assignments, quizzes, databases, etc. The primary focus of My-Moodle is to provide the activity-based modelling, in which the activities are segregated into sequences, which guides the learner in the form of learning path. Fig. 6.13 depicts the dashboard of My-Moodle.

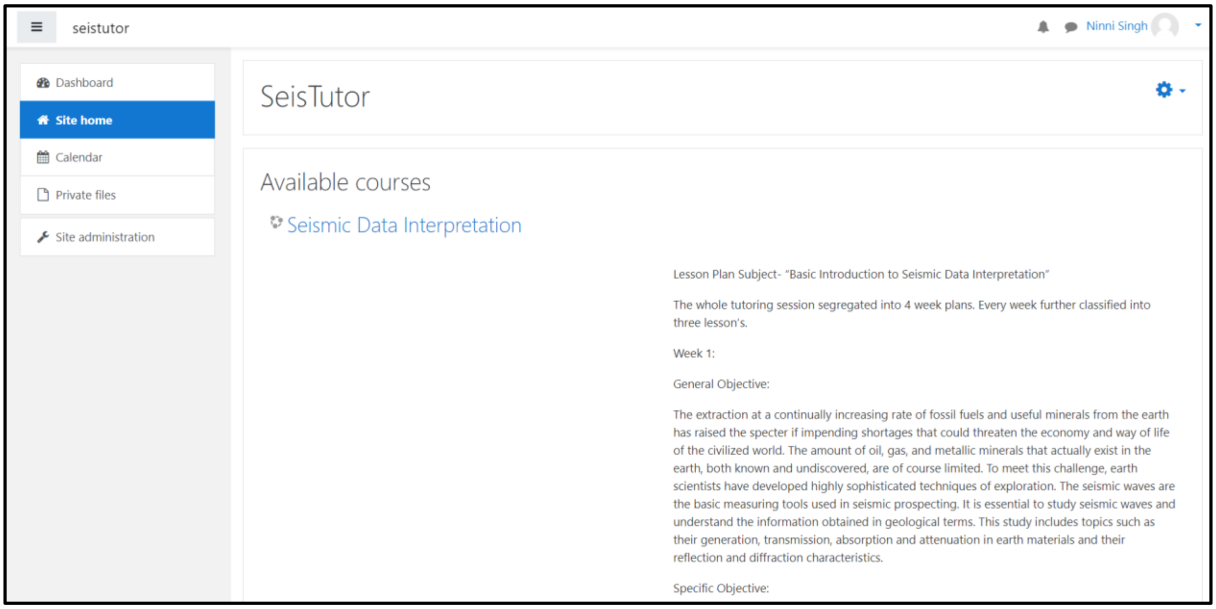


Figure 6-13 My-Moodle Dashboard

6.2.6.2. Course-Builder

Course builder helps the researcher to create their own learning environments, i.e. subject domain and learning quizzes, by using a rich feature set without any programming. The Course-builder is built on google app engine, therefore there is no limit on the number of registrations for learning the courses. It helps to keep the relationship with learners as well as with the teacher. Their vision is to provide broad access to education; that's why they collaborate with Openedx. Fig. 6.14 depicts the dashboard of Course builder.

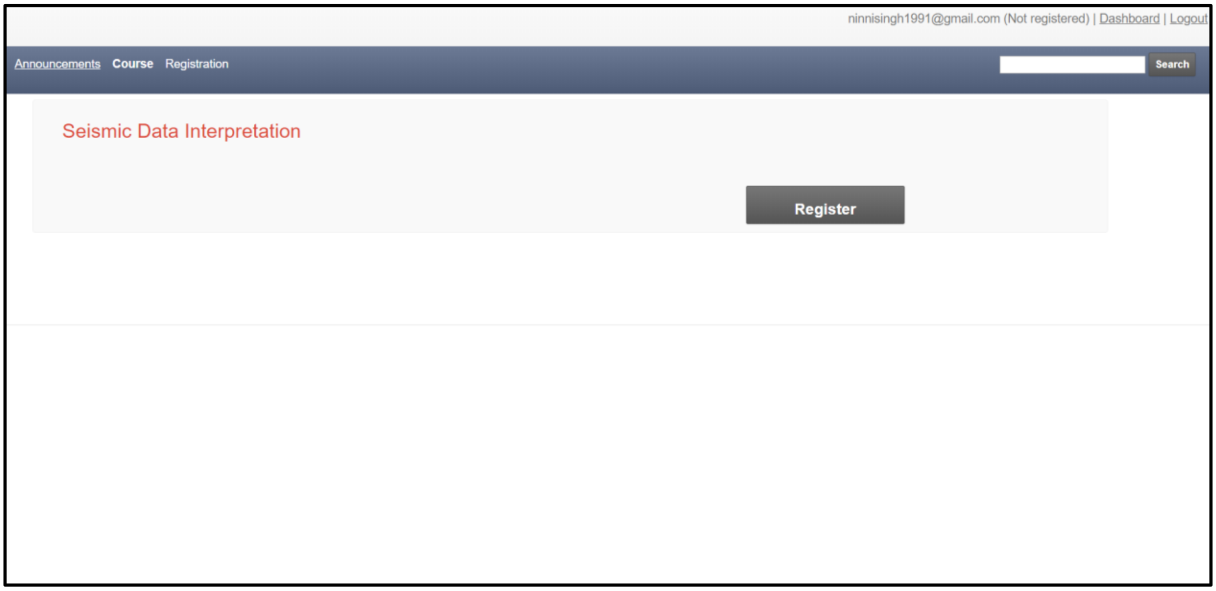


Figure 6-14 Course-Builder Dashboard

6.2.6.3.Teachable

Teachable is an open-source tutoring system, which provides a user-friendly learning environment. It provides a platform where subject experts can upload their learning content irrespective of what technology they have used. Teachable LMS is easily manageable, helps to build your brand, and it is best for the entrepreneur. However, they didn't focus on personalization and provide learning by adapting learner's grasping levels and preferred media. Fig. 6.15 depicts the dashboard of Teachable.

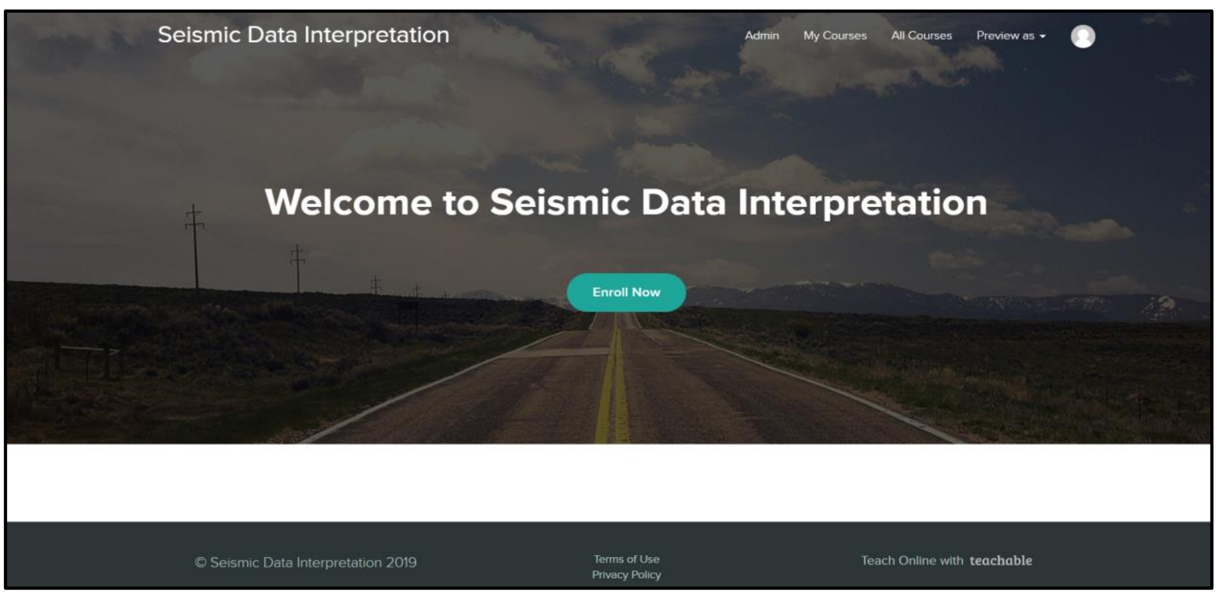


Figure 6-15 Teachable Dashboard

6.2.6.4. SeisTutor

The SeisTutor mimics the behaviour of the human tutor. The objective of SeisTutor to provide the Custom-Tailored learning environment for tacit subject domain “Seismic Data Interpretation”. Therefore, it incorporates computer science and artificial intelligence features, i.e. Custom-Tailored Curriculum Sequencing Module, Adaptive Tutoring Strategy Recommendation module and Performance Analyser Module (CNN based Emotion Recognition Module and Degree of Understandability Module). SeisTutor offers Learner-Centric learning material, i.e. the learning material is aligned as per learner learning style, learning profile or level and prior knowledge level. During ongoing tutoring, performance parameters, such as degree of engagement, emotions, quiz score and learning gain, is determined. Fig. 6.16 and 6.17 represents the learner dashboard.

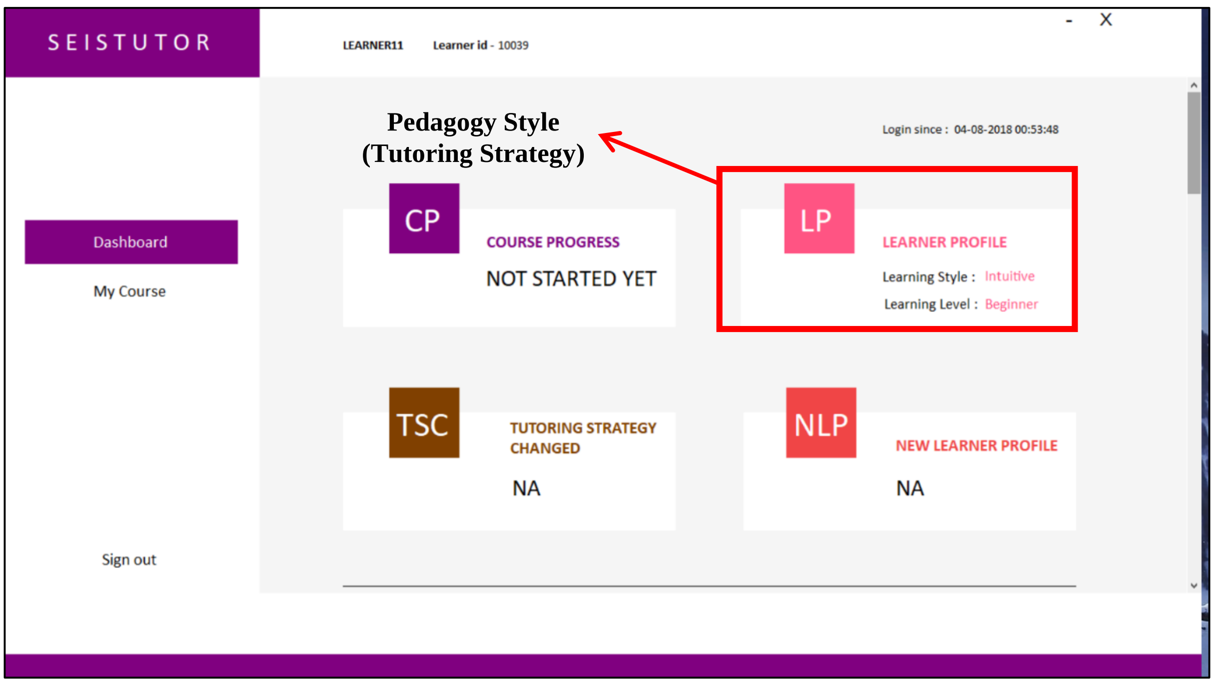


Figure 6-16 Learner dashboard using SeisTutor

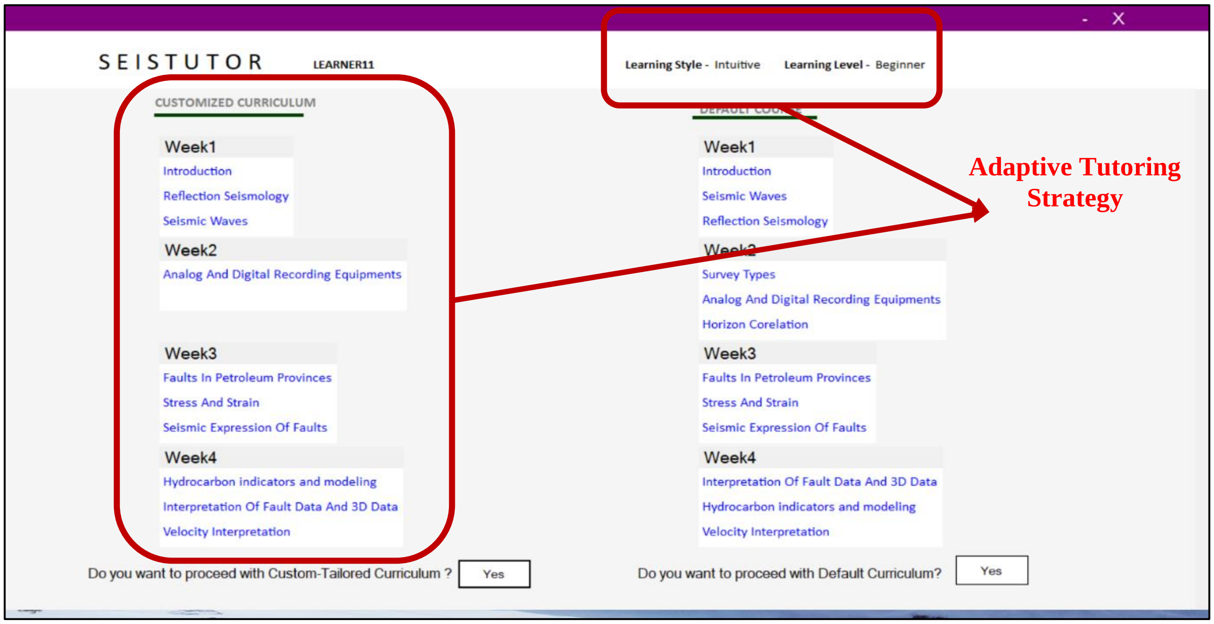


Figure 6-17 Custom-Tailored Curriculum offered to the learner.

Table 6-5 Summary of exiting Tutoring System

	Parameters	**My Moodle (LMS)**	**Course Builder**	**Teachable**	**SeisTutor**	**Conclusion Drawn**
GUI Based	Interactive GUI	Yes	Yes	Yes	Yes	All learning systems had done the significant work on the looks and felt of the tutoring system, which further helps to learn and made the system easy to use. Feedback report indicates that 71% of learner are highly satisfied with the SeisTutor GUI in comparison with My-Moodle (47%), Course builder (50%) and teachable (57%)
Learner-Centric Learning Environment	Learner Learning Style	No	No	No	Yes	Learner Centric learning environment is an essential aspect of the tutoring system because it makes the learning effective. But, as per the feedback received, it has been noticed that My-Moodle, Course Builder, and Teachable have given less emphasis on determining learner preferences learning style
	Learner Learning Level	No	No	No	Yes	
	Adaptive Tutoring Strategy	No	No	No	Yes	
	Custom-Tailored Curriculum	No	Separate course tracks features	No	Yes	

			are there, but they are not customized. They are pre-decided by the administrator based on the advance, and basic course opted by the learner.			and custom-tailored curriculum as compared to SeisTutor. However, some significant amount of work has been done by the course builder for identifying curriculum but still lacking behind to adapt the learner's prior knowledge and provide the personalized learning path. Feedback report indicates that 82% of learner are highly satisfied with the SeisTutor GUI in comparison with My-Moodle (38%), Course builder (4%) and teachable (4%)
Dynamic Profiling	Learner Pre-Test	No	No	No	Yes	SeisTutor carefully analyzes the learner psychological state and performance parameter before beginning learning session, after learning session and during the learning session. Thus, based on his/her interaction with the system SeisTutor dynamically analyze (learning gain) and update the learner profile. While other learning systems analyze the learner after the completion of the learning session. Feedback report indicates that 83% of learner are highly satisfied with the SeisTutor GUI in comparison with My-Moodle (46%), Course builder (27%) and teachable (23%)
	Learner Post-Test	Yes	Yes	Yes	Yes	
	Learner Psychological State during Ongoing Session	No	No	No	Yes	
Learning Content	Passive Learning Contents	Yes	Yes	Yes	No	SeisTutor offers learning material in total twelve pedagogy style, while My-Moodle, Course-Builder and teachable offer learning material only in one style. Feedback report indicates that 78% of learner are highly satisfied with the SeisTutor GUI in

						comparison with My-Moodle (14%), Course builder (16%) and teachable (3%)
Resolving Learner Query during Session	Handle Learner Problem during the session	No	Yes	Yes	No	SeisTutor and My-Moodle are unable to handle learner runtime issues, while Teachable and Course-Builder offer learners issue at runtime. Feedback report indicates that 68% of learner are highly satisfied with the SeisTutor GUI in comparison with My-Moodle (34%), Course builder (28%) and teachable (38%)
Navigation Support	Other parameters (navigation, modality, language, learning goal)	Yes	Yes	Yes	Yes	All learning system had done the significant work on providing the excellent navigational support in the tutoring system, which further helps to navigate from one module to other easily. Feedback report indicates that 68% of learner are highly satisfied with the SeisTutor GUI in comparison with My-Moodle (51%), Course builder (50%) and teachable (60%)
Learner Feedback	Learner Feedback	Yes	Yes	Yes	Yes	All learning system captures the learner feedbacks to analyze the effectiveness and comfort level of the learning system. Feedback report indicates that 65% of learner are highly satisfied with the SeisTutor GUI in comparison with My-Moodle (53%), Course builder (46%) and teachable (64%)

Here, the comparison is performed based on the functionality of the tutoring system listed in table 6.5. A total of 70 learners are registered themselves for learning the subject “Seismic Data Interpretation”. Teachable, Course-Builder, My-Moodle, and SeisTutor were evaluated by the same set of 70 learners, and their valuable feedbacks are discussed.

Feedbacks are ranked under three categories, i.e. strongly dissatisfied, neutral and strongly satisfied. Neutral indicates that the learner is not able to strongly mark their experience with the system. Strongly dis-satisfied indicates that the learner is not satisfied with the feature experienced by the learner during the learning session. Strongly satisfied indicates that the learner is satisfied with the feature experienced by the learner during the learning session. Learners are allowed to give their feedbacks ranges from 5 points Likert scale 1-5.

Summary

This chapter describes the statistical methods used for the evaluation of the SeisTutor. In the following chapter, the results and findings through the evaluation of SeisTutor are discussed.

Chapter 7 Results and Discussions

This chapter discusses the results obtained under the evaluation process of SeisTutor chapter. The statistical results and findings, have been discussed.

7.1 Analysis of Learner Performances

This analysis determines the overall learner performance. Learner performance (scores) in quizzes (Week-1 Week-2, Week-3, and Week-4) is analyzed and the average of the same is computed for both the groups i.e. Experimental and Control.

Table 7.1 and Table 7.2 shows, the average week wise learner's performances of both the groups (control and experiment) respectively.

Table 7-1 Overall performance of Control Group

S.N	Before Tutoring		During Tutoring				After Tutoring	
	Pretest Score	Learner Level (LL)	Week wise learner performance				Post Tutoring Score	Learner Level (LL)
			W1	W2	W3	W4		
L1	2.31	INT	3	2	3	4	3	INT
L2	2.31	INT	1	3	4	4	3	INT
L3	4.62	EXP	4	4	5	4	4.25	EXP
L4	2.31	INT	2	3	2	5	3	INT
L5	4.62	EXP	3	4	5	4	4	EXP
L6	0.38	BEG	4	4	3	4	3.75	EXP
L7	2.31	INT	3	3	4	5	3.75	EXP
L8	2.31	INT	2	4	4	5	3.75	EXP
L9	4.62	EXP	5	5	5	4	4.75	EXP
L10	2.69	INT	3	4	3	4	3.5	INT
L11	0.38	BEG	1	3	4	5	3.25	INT
L12	2.31	INT	4	4	4	5	4.25	EXP
L13	2.31	INT	2	3	5	4	3.5	INT
L14	2.31	INT	3	2	3	4	3	INT
L15	1.54	BEG	3	3	4	4	3.5	INT
L16	2.69	INT	4	5	4	5	4.5	EXP
L17	2.31	INT	3	4	3	4	3.5	INT
L18	2.31	INT	4	5	5	4	4.5	EXP
L19	0	BEG	3	4	4	3	3.5	INT
L20	2.69	INT	2	3	4	3	3	INT
L21	2.31	INT	2	3	3	4	3	INT
L22	0	BEG	3	3	3	4	3.25	INT
L23	2.15	INT	5	5	5	4	4.75	EXP
L24	2.31	INT	4	4	3	3	3.5	INT
L25	2.31	INT	3	3	3	4	3.25	INT
L26	0.38	BEG	4	5	4	3	4	EXP
L27	4.62	EXP	5	3	4	3	3.75	EXP
L28	2.31	INT	4	4	4	4	4	EXP
L29	4.62	EXP	4	4	4	4	4	EXP
L30	4.75	EXP	4	5	4	5	4.5	EXP

L31	3.5	INT	2	2	2	3	2.38	INT
L32	0.38	BEG	4	3	3	3	3.25	INT
Avg	2.41		3.22	3.63	3.75	4	3.65	

Table 7-2 Overall performance of Experiment Group

S.N	**Before Tutoring**		**During Tutoring**				**After Tutoring**	
	Pretest Score	**Learner Level (LL)**	**Week wise learner performance**				**Post Tutoring Score**	**Learner Level (LL)**
			W1	**W2**	**W3**	**W4**		
L1	2.69	INT	2	3	3	5	3.25	INT
L2	1.54	BEG	3	3	4	5	4	EXP
L3	1.92	BEG	4	4	5	3	4	EXP
L4	2.69	INT	5	4	4	4	4.25	EXP
L5	1.54	BEG	3	3	4	4	3.5	INT
L6	1.92	BEG	3	4	5	4	4	EXP
L7	0.38	BEG	4	5	3	5	4.25	EXP
L8	1.54	BEG	5	5	3	5	4.5	EXP
L9	1.15	BEG	5	4	4	3	4	EXP
L10	2.31	INT	3	3	4	5	3.75	EXP
L11	0.38	BEG	2	3	3	4	3	INT
L12	2.31	INT	2	3	4	5	3.5	INT
L13	1.15	BEG	5	5	3	4	4.25	EXP
L14	0.77	BEG	4	3	4	5	4	EXP
L15	1.15	BEG	3	5	3	4	3.75	EXP
L16	1.92	BEG	2	4	4	4	3.5	INT
L17	2.31	INT	3	4	5	5	4	EXP
L18	1.54	BEG	3	3	4	4	3.5	INT

L19	0.13	BEG	3	4	5	3	3.75	EXP
L20	0.77	BEG	2	3	5	5	3.75	EXP
L21	1.92	BEG	5	4	3	5	4.25	EXP
L22	3.43	INT	3	5	4	4	4	EXP
L23	0.77	BEG	5	4	5	3	4.25	EXP
L24	0.38	BEG	5	4	5	4	4.5	EXP
L25	4.23	EXP	3	5	4	5	4.25	EXP
L26	3.08	INT	4	5	5	5	4.75	EXP
L27	1.54	BEG	3	5	4	4	4	EXP
L28	2.69	INT	2	3	5	5	3.75	EXP
Avg	1.72		3.43	3.93	4.07	4.32	3.94	

Control Group:

The mean score performance of Week-1 is [3.22], Week-2 is [3.63], Week-3 is [3.74], and Week-4 is [4.00] as shown in Fig. 7.1 below. The performance graphs of learner's for week-1, week-2, week-3, and week-4 of the control group are shown in Fig. 7.2, Fig. 7.3, Fig. 7.4, and

Fig. 7.5, respectively.

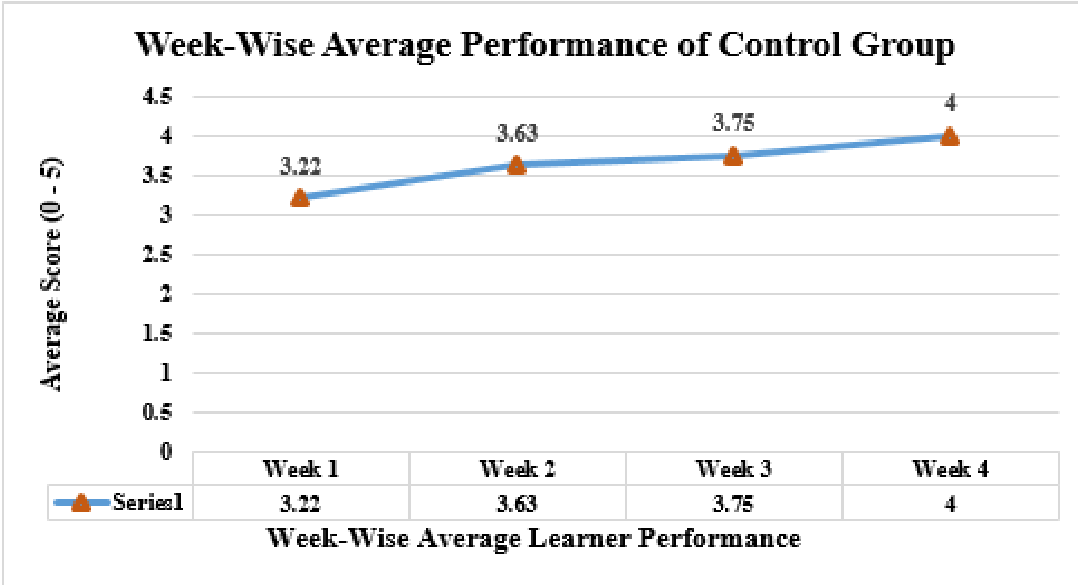


Figure 7-1 Average Learner Performance of Control Group

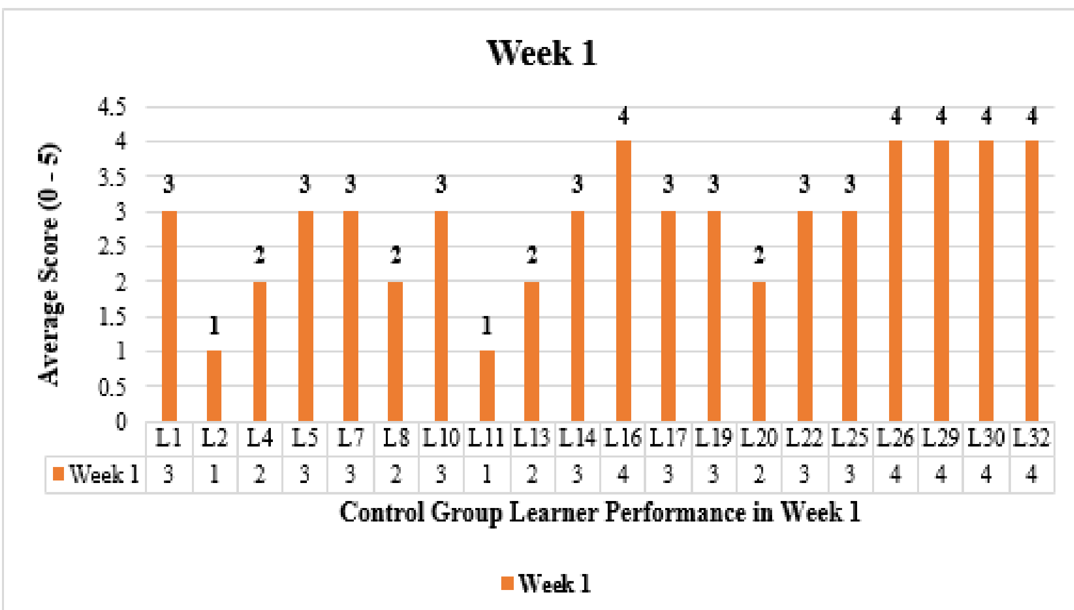


Figure 7-2 Control Group Learner Performance in Week 1

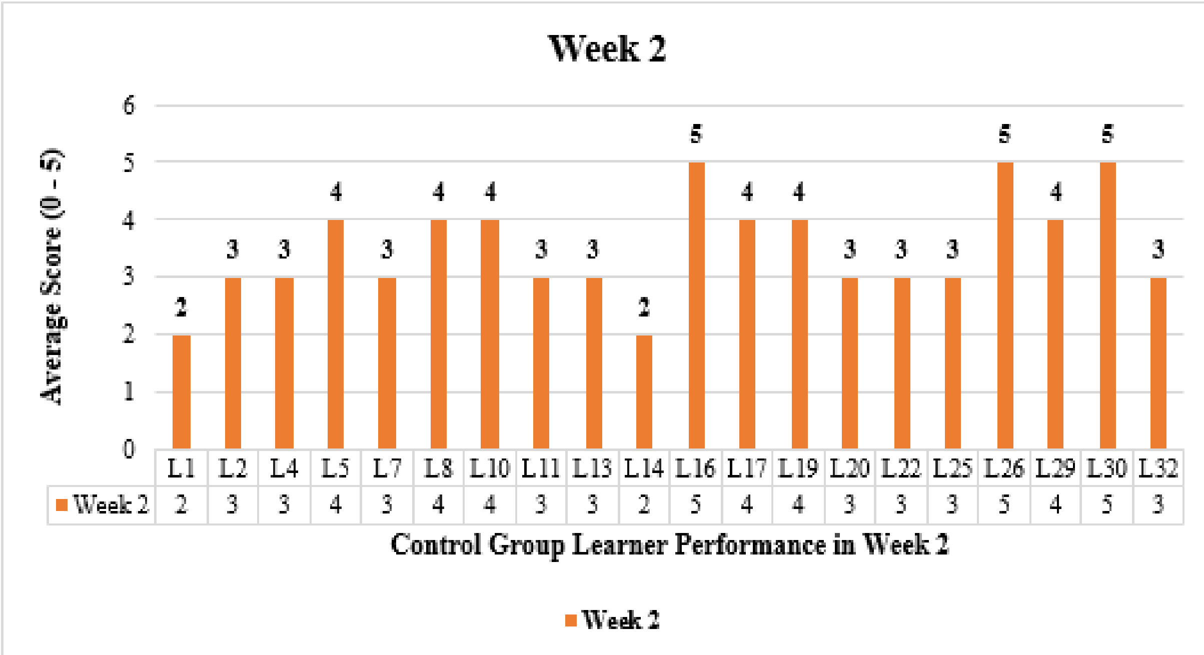


Figure 7-3 Control Group Learner Performance in Week 2

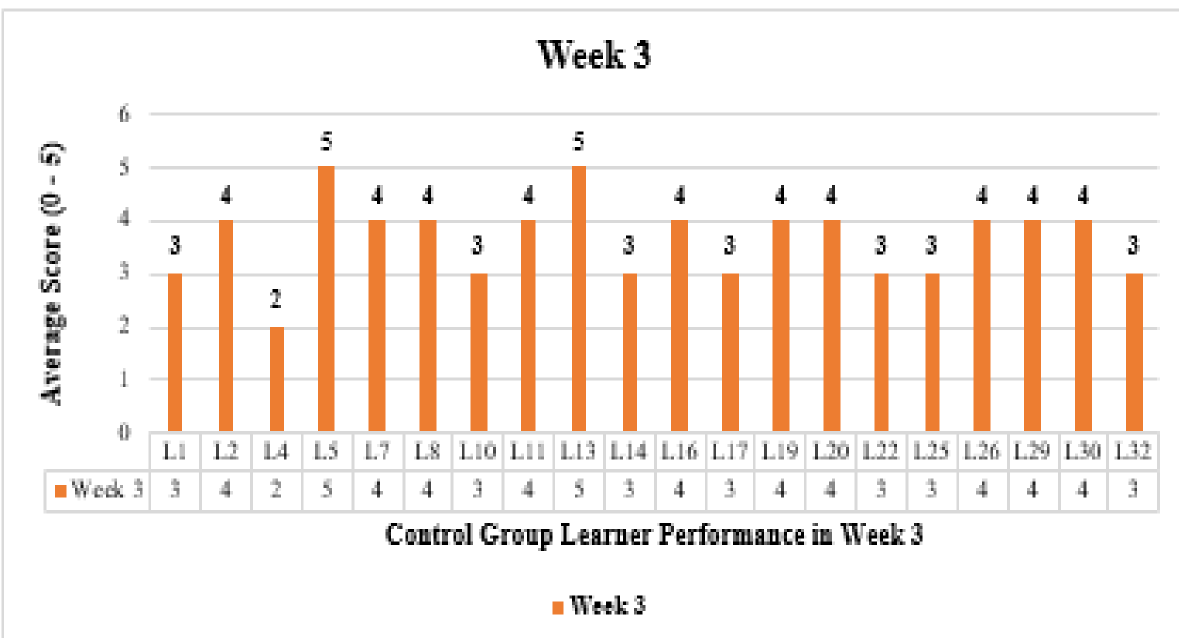


Figure 7-4 Control Group Learner Performance in Week 3

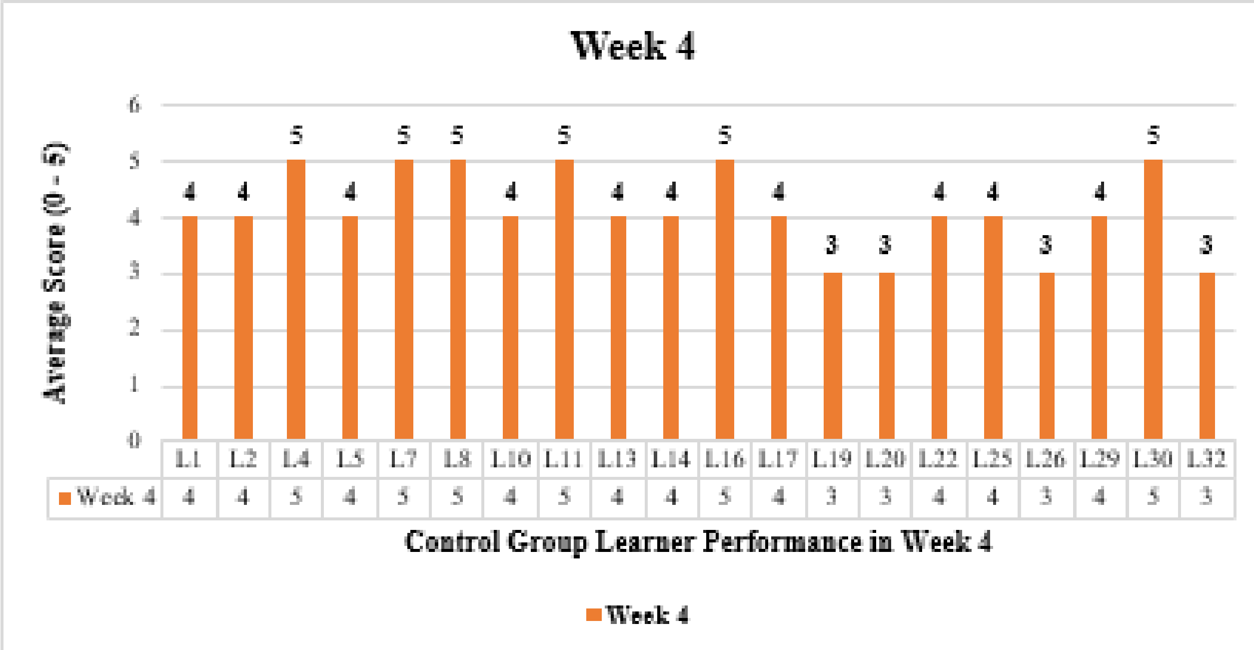


Figure 7-5 Control Group Learner Performance in Week 4

Experimental Group:

The mean score performance of the week-1 is [3.43], week-2 is [3.93], Week-3 is [4.07], and week-4 is [4.32] as shown in Fig. 7.6 below. The performance graphs of learner's for week-1, week-2, week-3, and week-4 of the experimental group are shown in Fig. 7.7, Fig. 7.8, Fig. 7.9, and Fig.7.10 respectively.

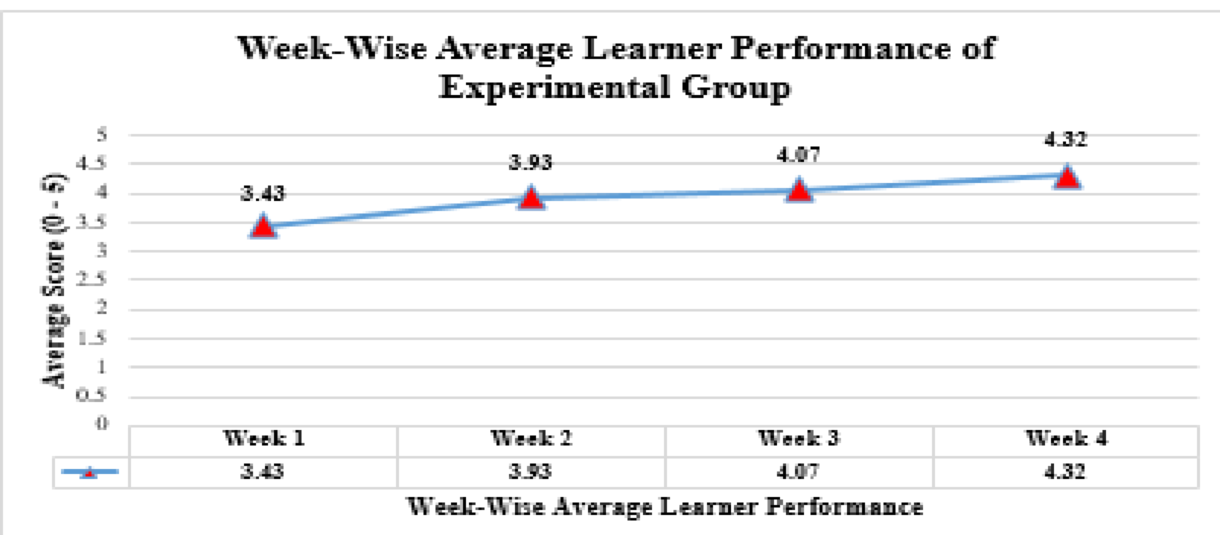


Figure 7-6 Average Learner Performance of Experimental Group

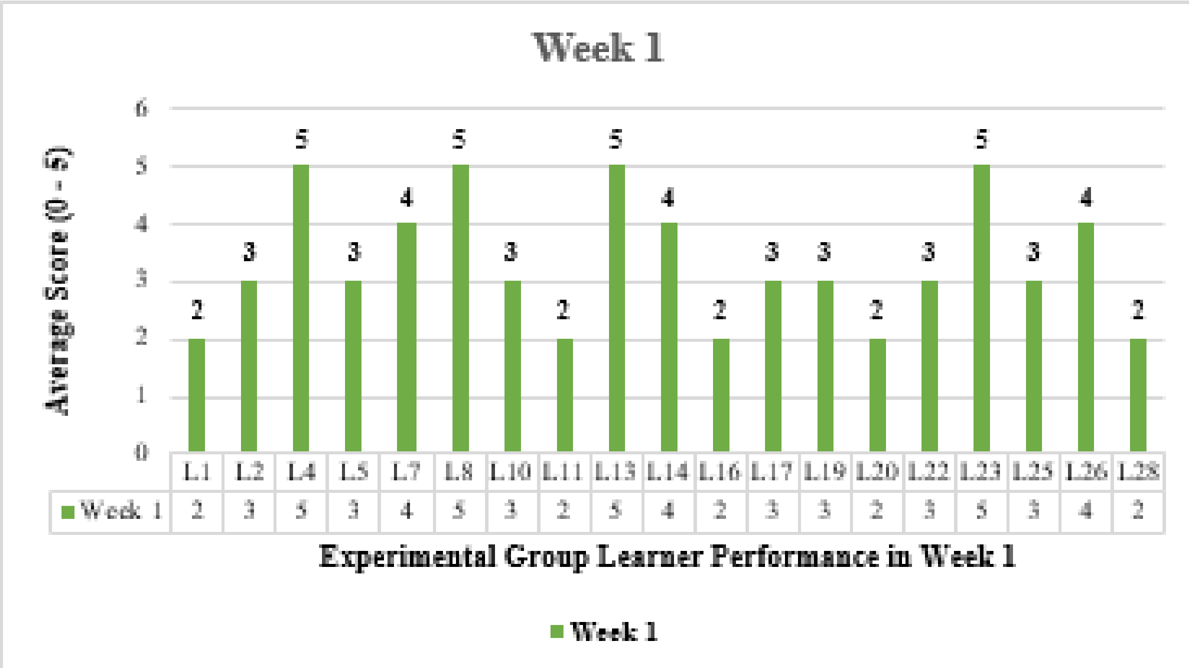


Figure 7-7 Experimental Group Learner Performance in Week 1

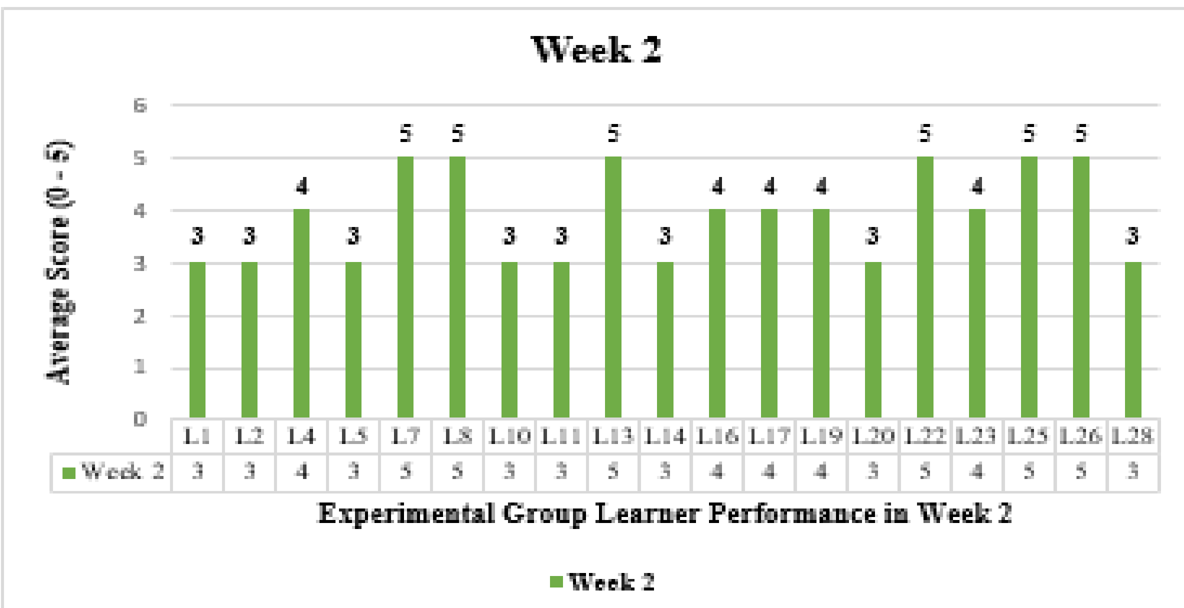


Figure 7-8 Experimental Group Learner Performance in Week 2

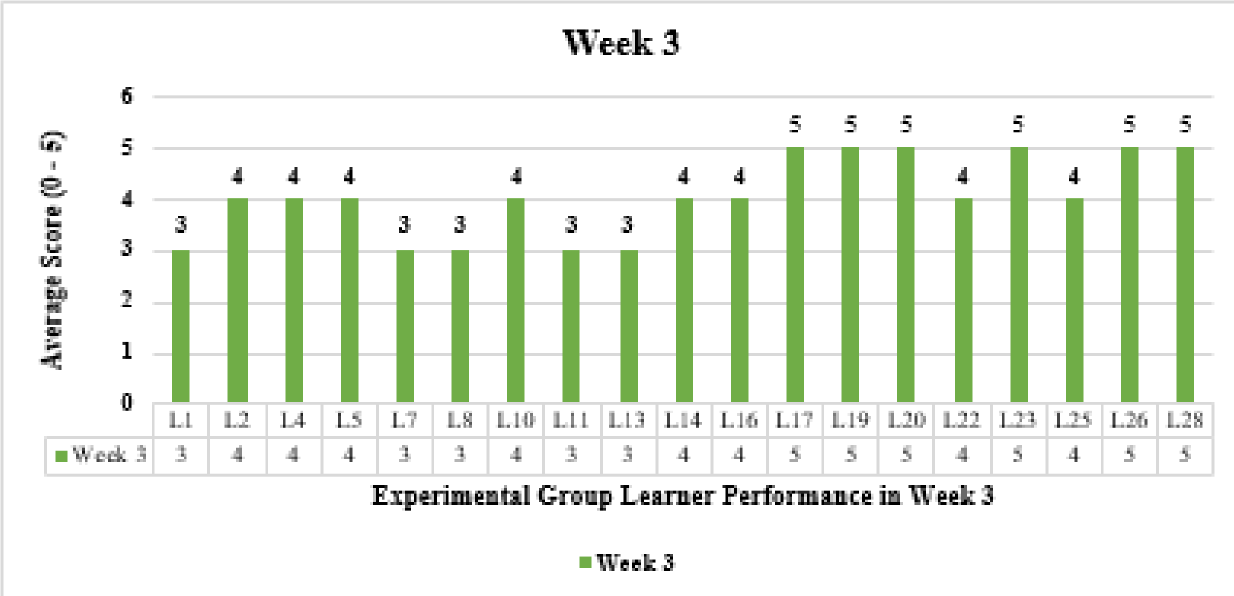


Figure 7-9 Experimental Group Learner Performance in Week 3

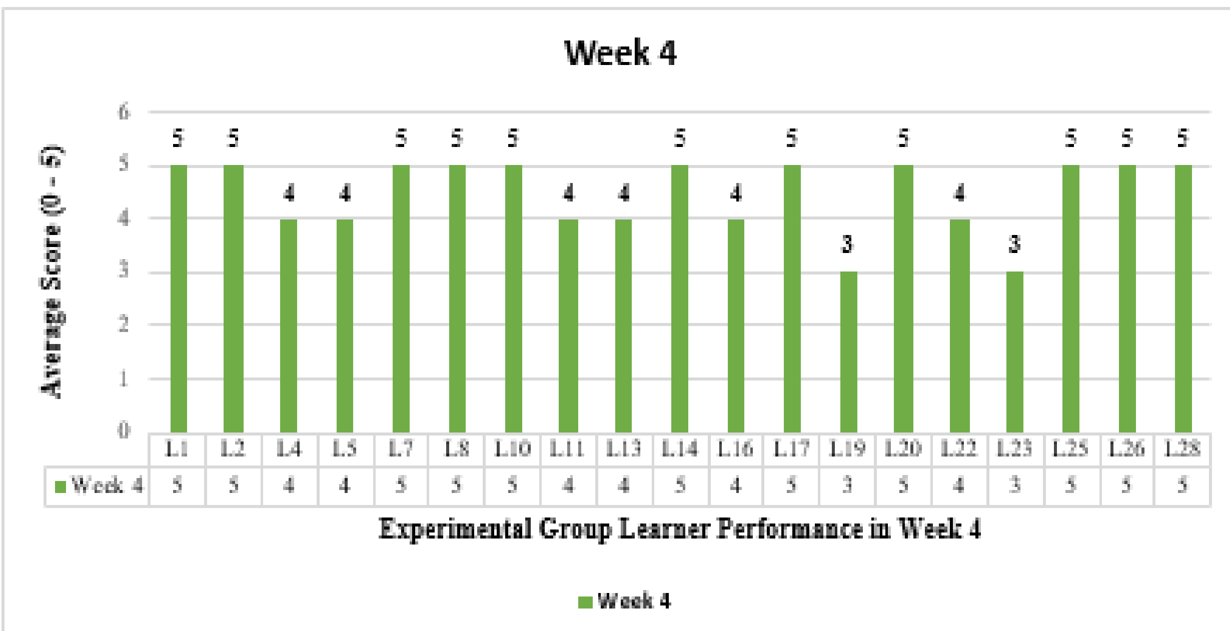


Figure 7-10 Experimental Group Learner Performance in Week 4

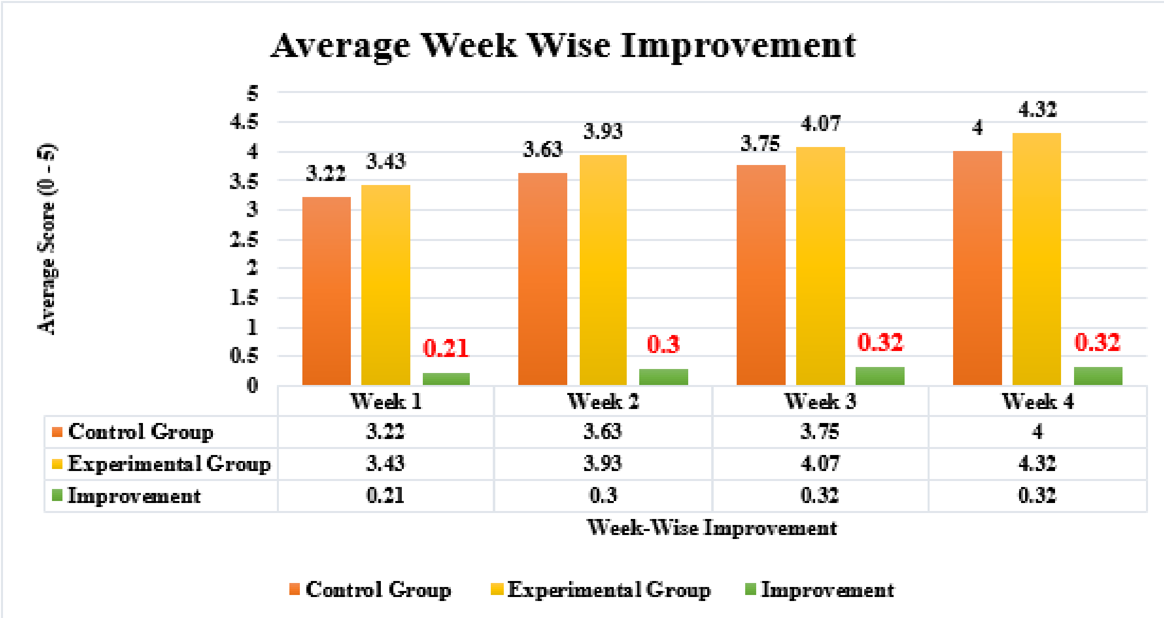


Figure 7-11 Average Week-Wise Improvement

The average week-wise learner's performance of both the groups is compared, the second group (experimental group) gradually shows the improvement as against the first group (control group) since starting from Week 1 to Week 4. The mean score improvements of Week-1 is [0.21], Week-2 is [0.3], Week-3 is [0.32], and Week-4 is [0.32]. From their mean score week-wise improvement, one can say with confidence that learning through adaptive Tutoring Strategy helps the learner to enhance the learner performance (see Fig. 7.11).

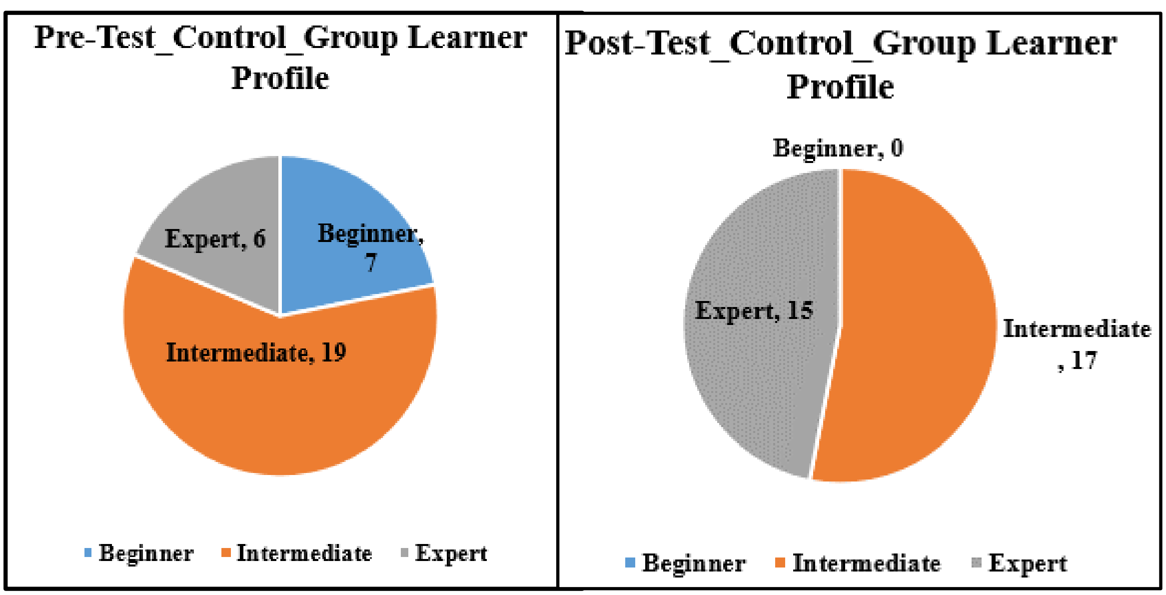


Figure 7-12 Learner Level before and after tutoring (Control Group)

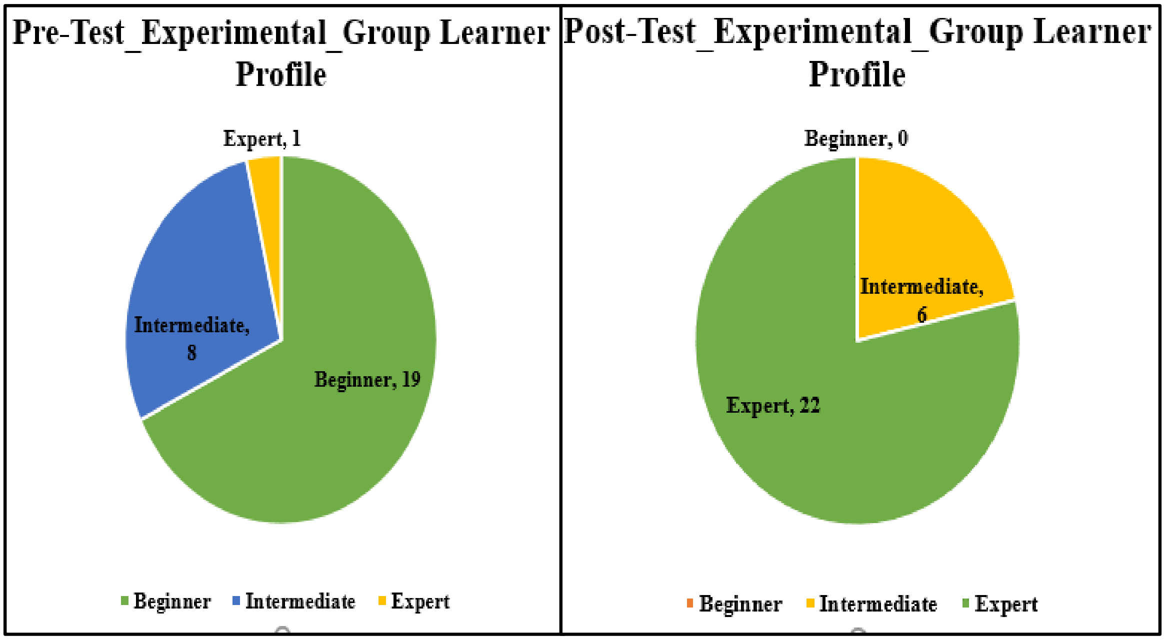


Figure 7-13 Learner Level before and after tutoring (Experimental Group)

Based on the performance of the learner in the pretest, SeisTutor categorizes the learners into the three groups, i.e. *Beginner*, *Intermediate*, and *Expert*. From the pretest scores of control group learners, it has been observed that initially, 7 learners belonged to the *Beginner* category, 19 learners belonged to the *Intermediate* category and 6 learners belonged to the *Expert* category. Learner's initial profile gets upgraded or downgraded based on their overall performance during the tutoring session. From the results it has been observed that, 7 learners initially belonged to the *Beginner* profile, out of which 4 get promoted to *Intermediate* and remaining 2 get promoted to the *Expert* profile (see Table 7.3).

Table 7-3 Learner Level before and after tutoring (Control Group)

S.N	Before Tutoring		After Tutoring		
	Learner Level	Learners	Beginner	Intermediate	Expert
1.	**Beginner**	7	0	4	3
2.	**Intermediate**	19	0	12	7
3.	**Expert**	6	0	1	5

Table 7-4 Learner Level before and after tutoring (Experimental Group)

S.N	Before Tutoring		After Tutoring		
	Learner Level	Learners	Beginner	Intermediate	Expert
1.	**Beginner**	19	0	4	15

2.	**Intermediate**	8	0	2	6
3.	**Expert**	1	0	0	1

Similarly, initially 19 learners belonged to the *Intermediate* profile. It has been observed that, out of 19 learners, 12 learners continue to remain at the same level (*Beginner*), while 7 of them, get promoted to *Expert* profile. Initially, 6 learners belonged to *Expert* profile, out of these 6 learners, 5 learners continue to remain at the same level (*Expert*) while only 1 learner gets downgraded to *Intermediate* profile.

Now considering the pretest scores of the second phase, it has been observed that initially, 19 learners belonged to the *Beginner* category, 8 learners belonged to the *Intermediate* category and 1 learner belonged to the *Expert* category.

Initially, 19 learners belonged to *Beginner* profile out of them 4 get promoted to *Intermediate* and remaining 15 get promoted to *Expert* profile (see Table 7.4). Similarly, initially, 8 learners belonged to the *Intermediate* profile out of them 2 learners continue to remain at the same level, while 6 learners get promoted to *Expert* profile. Initially, only 1 learner belonged to *Expert* profile and that learner remains at the same level.

Therefore, this can be concluded from the aforementioned analysis, that the learners, which belongs to Experimental group, improved their performance in terms of scores (shown in Fig. 7.12 and Fig. 7.13). Here, learner profile upgradation from their initial learning profile specifies the effectiveness of the learning program. i.e. Dynamic Profiling of the learner.

7.2. Predictive Statistical Analysis of Degree of Understanding Module

This section discusses the results and finding of the Predictive Analysis performed on the scores obtained by the learner in the Degree of Understanding Test.

Table 7.5 summarizes "degree of understanding computations" using 2×2 confusion matrix that portrays four possible circumstances.

Table 7-5 2×2 confusion matrix

True Positive **Condition:** Effective Impact correctly predicted	**False Positive** **Condition:** Negligible Impact incorrectly predicted
False Negative **Condition:** Effective Impact incorrectly predicted	**True Negative** **Condition:** Negligible Impact correctly predicted

Let first quantify the precision-recall and accuracy.

Precision: Proportion of positive cases predicted positively.

$$\boldsymbol{Precision = \frac{TP}{TP+FP}} \tag{7.1}$$

Recall: Proportion of positive cases predicted accurately (consider all the cases).

$$\boldsymbol{Recall = \frac{TP}{TP+FN}} \tag{7.2}$$

Accuracy: Proportion in which both positive and negative cases predicted accurately.

$$\boldsymbol{Accuracy = \frac{TP+TN}{TP+FN+FP+TN}} \tag{7.3}$$

Let the threshold value is 2 then Table 7.6 depicts the 2×2 confusion matrix

Table 7-6 2×2 confusion matrix when the threshold value is 2

True Positive **94**	**False Positive** **0**
False Negative **15**	**True Negative** **3**

From Equation 2, 3 and 4, the computed precision, recall and accuracy are as follows:

$$\boldsymbol{Precision = \frac{94}{94} \quad =\gg \ 1} \tag{7.4}$$

$$\boldsymbol{Recall = \frac{94}{94+15} \quad =\gg \ 0.8623} \tag{7.5}$$

$$\boldsymbol{Accuracy = \frac{94}{94+15+03} \quad =\gg 0.84} \tag{7.6}$$

Similarly, when the threshold value is 3, then Table 7.7 depicts the 2×2 confusion matrix

Table 7-7 2×2 confusion matrix when the threshold value is 3

True Positive **75**	**False Positive** **0**
False Negative **19**	**True Negative** **18**

From Equation 7.1, 7.2, and 7.3 the computed precision, recall and accuracy are as follows:

$$\boldsymbol{Precision} = \frac{75}{75} \quad \Rightarrow \quad \mathbf{1} \tag{7.7}$$

$$\boldsymbol{Recall} = \frac{75}{75+19} \quad \Rightarrow \quad \mathbf{0.7978} \tag{7.8}$$

$$\boldsymbol{Accuracy} = \frac{75}{75+19+18} \quad \Rightarrow \mathbf{0.67} \tag{7.9}$$

From equations 7.6, 7.7, 7.8, and 7.9, it has been observed from the obtained results is that when the threshold value increases, the recall and accuracy value is decreasing, but the precision value remains the same. Precision and Recall are inversely proportional to each other. The results from equations 7.4, 7.5 and 7.6, the prediction accuracy of the Degree of Understanding module is 84 %. It may get varied based on the threshold value.

7.3.Pre Tutoring and Post Tutoring Performance

This section identifies and discusses the results of the groups that prompts enhancements in learner's learning/aptitudes (i.e. test results). The ANOVA is performed on the pretest and posttest score of learners of both the groups. The inference on the obtained results are as follows.

The F-ratio of the ANOVA test for the control group is F_calc= 21.68911 at $\alpha=0.05$, where α is a significant level, while the tabulated value is F_α = 4.00 (From the F-Table). Here F_calc>F_α, with the degree of freedom being v1 =1 and v2 = 62 (see Table 7.10). The learning gain has been shown in Table 7.8. Hence, the null hypothesis H_0 rejected and the alternative hypothesis, H_1: $\mu 1 < \mu 2$ is accepted. It indicates that there is a significant difference between scores of pretest and posttest tests. Hence, it is deduced that the difference in the posttest and pretest is significant and the training is effective for the control group.

Similarly, the F-ratio of the ANOVA test for the experimental group is F_calc= 119.7141 at $\alpha=0.05$, where α is a significant level, while the tabulated value is F_α = 4.03 (From the F-Table). Here F_calc> F_α, with the degree of freedom being v1 =1 and v2 = 54 (see Table 7.9). Hence the null hypothesis Ho rejected and the alternative hypothesis H1: $\mu 1 < \mu 2$ is accepted. It indicates that there is a significant difference between pretest and posttest tests. Hence, it is deduced that the difference in posttest and pretest is significant, and the training is effective for the experimental group. The learning gain has been shown in Table 7.8.

The participant's performance for both the phases reject the null hypothesis, which means training provided in both the groups is effective. However, this research aims to identify that which phase or group of training has a higher impact on enhancing the overall learning gain. The participants of the experimental group receive Custom-Tailored Curriculum Sequenced learning material(based on their prior/previous knowledge), learner's facial expressions are captured (ongoing learning session), and degree of the understanding score is determined, while these features enabled the learning environment is not offered to the participants of the control group. Therefore, to conclude, F_calc of both the groups are compared. F_calc of experimental group ($119.7141 - 21.68911 = 98.02499$) is higher than F_calc of the control group. Thus, the experimental group reports a significant difference in the posttest and pretest scores and provides more effective training than the control group.

Table 7-8 Data of pretest and posttest in terms of learning gain

System	Total Participants	Pre-Tutoring Test Score	Post-Tutoring Test Score	Mean Learning Gain
Experimental Group	28	1.72	3.94	44.4 %
Control Group	32	2.41	3.65	24.8 %

Table 7-9 Data of pretest and posttest in terms of learning gain Experimental Group

Source of variation	SS	DF	VS	F-ratio	5% F-limit (From the F table)
Between Sample	68.86446	(2-1)=1	68.86446	119.7141	F (1, 54) = 4.03
Within Sample	31.06302	(56-2)= 54	0.575241		
Total	68.86446	(56-1)= 55			

Table 7-10 Data of pretest and posttest in terms of learning gain Control Group

Source of variation	SS	DF	VS	F-ratio	5% F-limit (From the F table)
Between Sample	24.88763	(2-1)=1	24.88762656	21.68911	F (1, 62) = 4.00
Within Sample	71.1432	(64-2)= 62	1.147470917		
Total	96.03082	(64-1)= 63			

7.4. Kirkpatrick Four Stage Evaluation

This section identifies, discusses and compare the obtained results based on the 4 phases of the Kirkpatrick model namely, learner's reactions, comfort level, behavior and overall results. A four phase evaluation is performed on learner's emotion, pretest score, posttest scores, quizzes and feedback that belonged to both the groups. The phase-wise inference on the obtained results are as follows.

7.4.1. Kirkpatrick phase 1: Evaluation of Reaction:

The Learner reaction towards the learning content is gauged using CNN based Emotion Recognition Module. The Min-Max normalization performs a linear transformation on the original scores and fits the scores in the range of [0-10]. To maintain the uniformity of score normalization is performed.

Table 7-11 Descriptive Statistics of Psychological parameter of the learner for Experimental Group

Emotions	Mean	Std. Deviation	Mean %
Happy	4.4174	29.6357	44.1
Sad	2.4272	24.9175	24.2
Surprise	3.2275	28.2939	32.2
Fear	3.0612	26.8571	30.6
Angry	3.6728	26.1069	36.7
Neutral	4.0389	26.6193	40.3

The emotions of the learner are determined only for the participants, who have been involved in the Experimental group evaluation. Thus the average mean score percentage of maximum emotion occurrence is shown in table 7.11. The result of 28 participants is shown in table 7.11, in which 44 % of emotion are happy, 40 % of emotion are neutral, 36% of emotion are angry, 32 % of emotion are surprise, 30 % of emotion are fear and 24% of emotion is sad. Thus, from the result, the maximum emotion observed, is happy (44 %), which specifies that the 44 % of learners are happy with the provided learning content, and teaching process (pedagogy).

7.4.2. Kirkpatrick phase 2: Evaluation of Learning

This phase quantified the learner's overall learning, i.e. Learning Gain. Eqn. 7.10 is used for computing learning gain. The inferences on the results are as follows.

$$\boldsymbol{Learning\_Gain} = \ (\boldsymbol{PostTest\_Score_L} - \boldsymbol{PreTest\_Score_L}) \quad (7.10)$$

Table 7-12 Learner's Learning Gain

Study Cases	**No of Participants (n)**	**Learning Gain**		
		Mean	**Standard deviation**	**Mean %**
Experiment Group	28	2.2170	1.02795	44.34%
Control Group	32	1.2793	1.37034	24.8%

The average learning gain of participants in the experimental group is 44.34 %, and for the control group, is 24.8%. Thus, it has been concluded that if the learning material is offered as per learner's inclination with an exclusively designed curriculum based on their prior knowledge, then the proposed SeisTutor succeeds in enhancing the learner interest which indirectly enhances the overall learning gain (see Table 7.12).

Table 7.12 describes the progressive learning gain of 44.34% among learners that participated in the experimental group. Furthermore, this data (learning gain) is used for correlation analysis, i.e. Bivariate Pearson Correlation. This test is performed between the learning gain and the degree of understanding score of experimental group. As described in section 4, the Performance Analyzer Module is implemented for determining the degree of understanding. But this module is not offered to the control group. Therefore, this correlation analysis aims to determine the correlation between learning gain and the degree of understanding score. If there is a correlation, then from the law of symmetry, i.e. $if, A \in B\ and\ B \in C\ then, A \in C,$ one can say with confidence that if this test is offered to the control group, then in that case also the participants of the experimental group having a higher degree of understanding score (against the control group).

Table 7-13 Average Mean Score of Learning Gain & Degree of Understanding

Parameters	No. of Participants (n)	Learning Gain		
		Mean	**Standard deviation**	**Mean %**
Learning Gain	28	2.2170	1.02795	44.34%
Degree of Understanding	28	2.5467	1.31201	50.9%

Table 7-14 Correlation Matrix between Learning Gain and Degree of Understanding

Parameters		Learning Gain	Degree of Understandings
Learning Gain	Pearson correlation	1	0.484**
	Sig. (2-tailed)		0.009
	N	28	28
Degree of Understanding	Pearson correlation	0.484**	1
	Sig. (2-tailed)	.009	
	N	28	28

**. Correlation is significant at the 0.01 level (2-tailed).

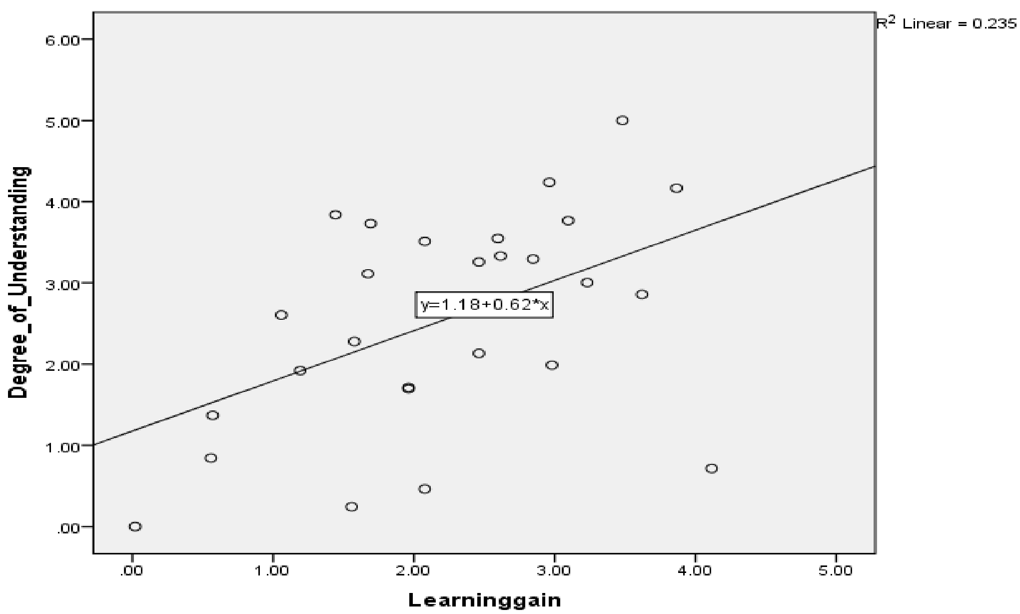


Figure 7-14 Linear Relationship with Learning Gain and Degree of Understanding

Here the correlation of Learning gain by itself is 1; this is due to a variable or parameter is perfectly interrelated with itself. The Pearson correlation of learning gain with the Degree of understanding is 0.484 with a 2 tailed significance, i.e. P-value is less than 0.05. Thus, it has been concluded that Learning gain and Degree of Understanding having a statistically significant linear relationship. $(P < 0.05)$ (see Fig. 7.14 and Table 7.14).

7.4.3. Kirkpatrick phase 3: Evaluation of Behaviour:

Based on learner feedback, this phase quantifies/assesses the learner's behaviour towards, Effectiveness, Adaptation (incorporated artificial intelligence features), overall support, learner comfort level and Custom Tailored Curriculum Sequencing.

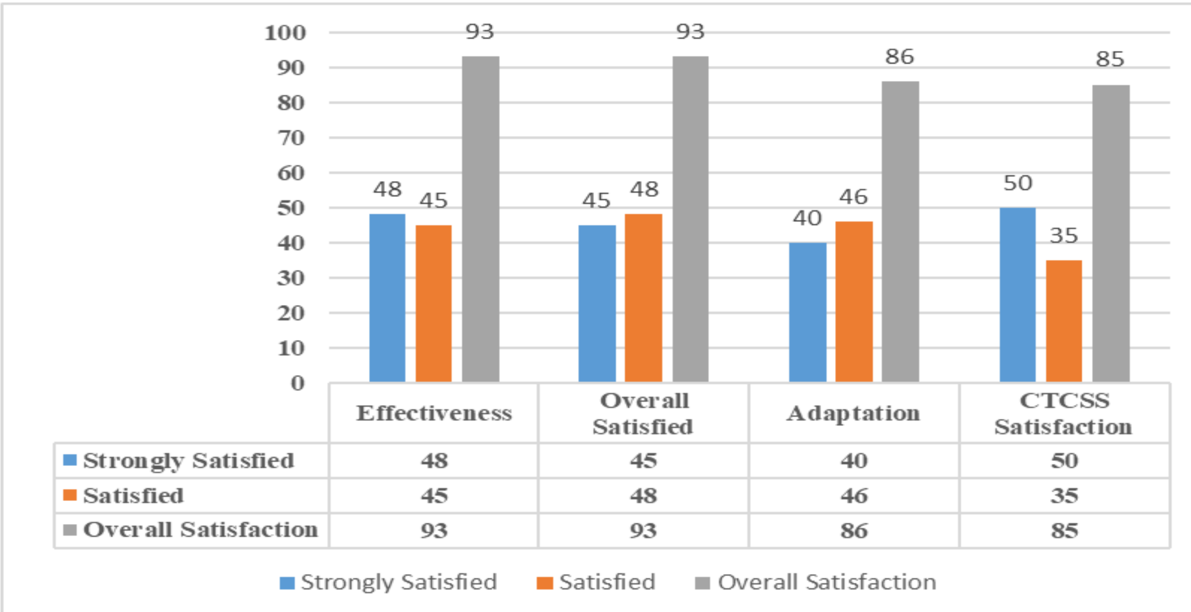


Figure 7-15 Evaluation of Learner Behavior based on Learner Feedbacks

As soon as the learner completes all the learning concepts of each week, SeisTutor requests the learner to give their feedback. In this section, a conclusion from the learner's feedbacks is drawn. The learners are considered as an impeccable part of this evaluation. The overall satisfaction with SeisTutor was around 93%, out of which 45% were strongly satisfied, and 48% were satisfied as well (see Figure 7.25, Table 7.15 in appendix 2). It has been also observed that learners, learning became productive with the SeisTutor.

Table 7-15 Learner Feedback on effectiveness of SeisTutor

22 questions were asked about the impact of the intelligent features provided by SeisTutor, the same has been collected and summarized in Table 7.16 (appendix 2). As some intelligent features are not provided to the control group participants (Custom-Tailored Curriculum Sequencing Module, Emotion Recognition Module and Degree of Understanding). Thus, feedbacks of 28 learners have been taken into consideration from experimental group participants.

Most of the participants were happy with the adaptive tutoring strategy provided by the system with 86% satisfaction, which includes 46% who were satisfied and 40% who were strongly satisfied. The 85% of participants felt that learning from their own learning experience make them perform better in which 40% who were strongly satisfied and 45% that were satisfied. The 85 % of participants were happy with the recommended exclusive curriculum with the system, which includes 35% were satisfied and 50% were strongly satisfied. 92% of participants agreed that understanding test at each week corresponds to the lessons taught, in which 39% strongly agreed, and the rest 53% agreed as well. At last, 82% participants agreed that CNN based Emotion Recognition module accurately determined their emotions during learning, in which 39% were strongly agreed and 43% were satisfied as well.

Table 7-16 Learner Feedback on Adaptation of SeisTutor

The overall support provided by SeisTutor to the learning process was assessed through the learner's feedback questionnaire answered by 60 participants (see Table 7.17 in appendix 2). The analyzed results showed that 87% of the participants are happy with the overall SeisTutor supports, with 47% -satisfied and 40% -strongly satisfied. In addition to that, 78% of the participants are happy with the system navigation support enabled to find the needed information with 43% - satisfied and 35% - strongly satisfied.

Table 7-17 Learner Feedback on SeisTutor ongoing Learning Support

The usefulness of the Learning contents such as content explanations, revisions, presented quizzes, and the question hints in the learning process evaluated in Table 7.18. The questionnaire feedback results show that, 85% students were happy with the content explained by SeisTutor with 47% satisfied and 38% strongly satisfied. Moreover, 78% of students showed their interest and agreed that the tutoring resources were adequate with 35% - strongly satisfied and 43% - satisfied. It is clear that the quizzes and hints were realistic and focused on the learning contents provided by the SeisTutor.

Table 7-18 Learner Feedbacks on learning material, quizzes and overall SeisTutor support

From the overall evaluation of the SeisTutor, on learner's feedbacks, reveals that 86% of learners agreed that tutoring was provided as per their learning profile or level, learning style and prior knowledge. Most of the learners or participants liked the artificial intelligence features such as the automatic recommendation of Adaptive Tutoring Strategy, dynamically assessing the learner performance, Emotion Recognition and measurement of their Degree of Understandability score.

The learner's feedbacks were retrieved and analyzed in a free form fashion. Some learners put their suggestions to improve the productivity of SeisTutor. Most of the suggestions were general and related to the improvement of the system, and 08 were negative regarding the improvement of the quality of learning contents, improving the quality of the video lessons, and hints provided by the system. At last, through the overall evaluation of SeisTutor, 87% of learners agreed that they have improved their learning performance and outcomes.

7.4.4. Kirkpatrick phase 4: Evaluation of Results:

This phase quantified the overall results in terms of effective learning. A Paired Sample T-test is performed on the learner's performance parameters, i.e. pretest and posttest scores of participants involved in both the studies (Experimental and Control groups). The Hypothesis for inferencing the results is described as follows.

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

Hypothesis-Case-1.0: The participants involved in the Experimental group have similar pretest and posttest mean scores (negligible performance improvement).

Hypothesis-Case-1.1: The participants involved in the Experimental group have different pretest and posttest mean scores (effective performance improvement).

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

Hypothesis-Case-2.0: The participants involved in the control group have similar pretest and posttest mean scores (negligible performance improvement).

Hypothesis-Case-2.1: The participants involved in the control group have different pretest and posttest mean scores (effective performance improvement).

The calculated T value (T_{Stats},) for the experimental group is 11.410, $P < 0.01$ (see Table 7.21). On an average posttest score was 2.21786 points which are higher than pretest scores. Here the calculated T_{Stats} is greater than $T_{critical}$, thus hypothesis 1.0 is rejected. From Table 7.21 and 7.19, it has been concluded that there is a significant difference between Pretest and Posttest scores.

The calculated T value (T_{Stats},) for the control group is 5.312, $P < 0.01$ (see Table 7.22). On an average posttest score was 1.24719 points which are higher than pretest scores. Here the calculated T_{Stats} is greater than $T_{critical}$. Thus hypothesis 2.0 are rejected. From Table , 7.20 and 7.22 it has been concluded that there is a significant difference between Pretest and Posttest score.

Null hypothesis have been rejected by both the groups that means both the groups provide adequate training. But the aim of this analysis is to identify, which group is having a higher impact on enhancing the overall learning gain. For concluding the aim, T_{Stats} of both the groups are compared. T_{Stats} of experimental group is higher than T_{Stats} of control group. Thus, the experimental group is having a significant difference in the posttest and pretest scores and also provides more effective training than the control group.

Table 7-19 Statistical results of Paired Sample T-Test of Experimental group

Comparison Item	**Learning Mode**			
	Mean	**N**	**Std. Deviation**	**Std. error Mean**
Posttest of Experimental group Participants	3.9375	28	.39455	.07456
Pretest of Experimental group Participants	1.7196	28	.99740	.18849

Table 7-20 Statistical results of Paired Sample T-Test of Control group

Comparison Item	**Learning Mode**			
	Mean	**N**	**Std. Deviation**	**Std. error Mean**
Posttest of Control group Participants	3.6525	32	.58915	.10415
Pretest of Control group Participants	2.4053	32	1.39565	.24672

Table 7-21 Paired-Sampled-T-Test results of Experimental group

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

Table 7-22 Paired-Sampled-T-Test results of Control group

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

This analysis concludes that the Experimental group surpasses the Control group as it provides Custom-Tailored Designed Curriculum, identify the learner's emotions during learning process and compute the overall degree of understanding, which fulfil the learner's requirements.

7.5. Comparative analysis of performance between the proposed Learner-Centric tutoring system "SeisTutor" with Existing online Tutoring System

A comparative analysis is performed between the proposed SeisTutor with the three open source online learning system (My-Moodle, Course-Builder and Teachable). The inferences drawn from the learner's feedback are described below. Table 7.23, Table 7.24, Table 7.25 and Table 7.26 indicates the analysis of responses to Learner feedback questionnaire for My-Moodle, Course-Builder, Teachable and SeisTutor, respectively.

Table 7-23 Analysis of responses on Learner feedback questionnaire: My-Moodle

Parameters	**Strongly-Dissatisfied (%)**	**Neutral (%)**	**Strongly-Satisfied (%)**
GUI Based	24	30	46
Learner-Centric Learning Environment	45	17	38
Dynamic Profiling	35	18	46
Learning Content	50	36	14
Resolving Query during the session	53	13	34
Navigation support	22	27	51
Learner feedback	33	14	53
Cumulative Percentage (%)	37.42	22.22	40.36

Table 7-24 Analysis of responses on Learner feedback questionnaire: Course-Builder

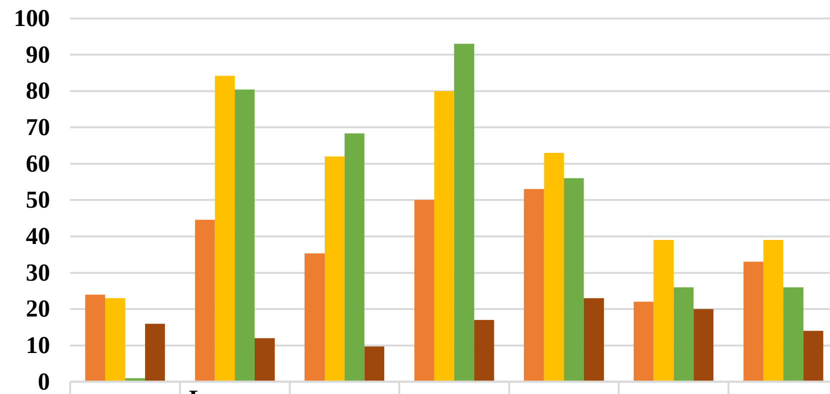
Parameters	**Strongly-Dissatisfied (%)**	**Neutral (%)**	**Strongly-Satisfied (%)**
GUI Based	23	31	46
Learner-Centric Learning Environment	84	12	4
Dynamic Profiling	62	11	27
Learning Content	80	4	16
Resolving Query during the session	63	9	28
Navigation support	39	11	50
Learner feedback	39	15	46
Cumulative Percentage (%)	55.74	13.33	30.92

Table 7-25 Analysis of responses on Learner feedback questionnaire: Teachable

Parameters	**Strongly-Dissatisfied (%)**	**Neutral (%)**	**Strongly-Satisfied (%)**
GUI Based	1	43	56
Learner-Centric Learning Environment	80	16	4
Dynamic Profiling	68	9	23
Learning Content	93	4	3
Resolving Query during the session	56	6	38
Navigation support	26	14	60
Learner feedback	26	10	64
Cumulative Percentage (%)	50.10	14.47	35.43

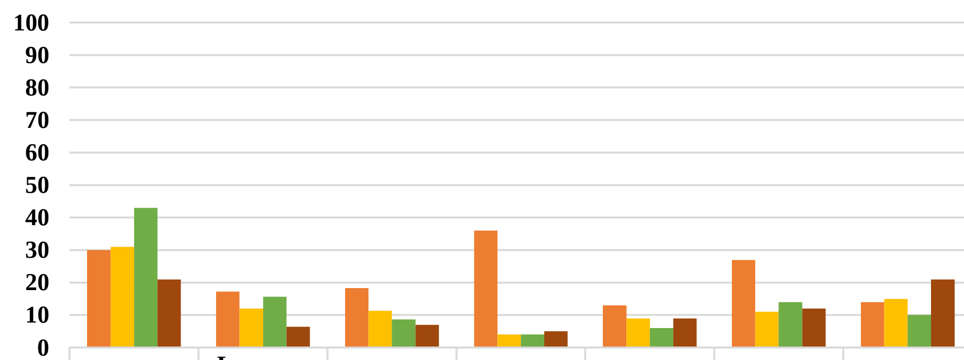
Table 7-26 Analysis of responses of Learner feedback questionnaire: SeisTutor

Parameters	**Strongly-Dissatisfied (%)**	**Neutral (%)**	**Strongly-Satisfied (%)**
GUI Based	16	21	71
Learner-Centric Learning Environment	12	6	82
Dynamic Profiling	10	7	83
Learning Content	17	5	78
Resolving Query during the session	23	9	68
Navigation support	20	12	68
Learner feedback	14	21	65
Cumulative Percentage (%)	16	12	74



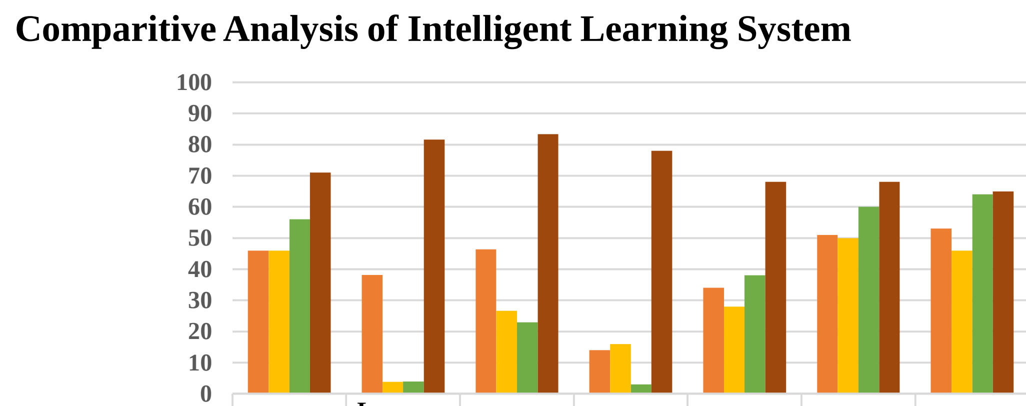
	GUI Based	Learner-Centric Learning Environment	Dynamic Profiling	Learning Content	Resolving Query during session	Navigation support	Learner feedback
MYMoodle_ Strongly-Dissatisfied	24	45	35	50	53	22	33
CourseBuilder_Strongly-Dissatisfied	23	84	62	80	63	39	39
Teachable_Strongly-Dissatisfied	1	80	68	93	56	26	26
SeisTutor_Strongly-Dissatisfied	16	12	10	17	23	20	14

Figure 7-16 Comparative studies of existing tutoring system with SeisTutor on Strongly Dis-satisfaction level



	GUI Based	Learner-Centric Learning Environment	Dynamic Profiling	Learning Content	Resolving Query during session	Navigation support	Learner feedback
MYMoodle_ Neutral	30	17	18	36	13	27	14
CourseBuilder_Neutral	31	12	11	4	9	11	15
Teachable_Neutral	43	16	9	4	6	14	10
SeisTutor_Neutral	21	6	7	5	9	12	21

Figure 7-17 Comparative studies of existing tutoring system with SeisTutor on Neutral Level



	GUI Based	Learner-Centric Learning Environment	Dynamic Profiling	Learning Content	Resolving Query during session	Navigation support	Learner feedback
MYMoodle_ Strongly-Satisfied	46	38	46	14	34	51	53
CourseBuilder_Strongly-Satisfied	46	4	27	16	28	50	46
Teachable_Strongly-Satisfied	56	4	23	3	38	60	64
SeisTutor_Strongly-Satisfied	71	82	83	78	68	68	65

Figure 7-18 Comparative studies of existing tutoring system with SeisTutor on Strongly Satisfaction level

Fig. 7.21, Fig. 7.22 and Fig. 7.23 demonstrate the comparative analysis of the tutoring systems (Teachable, Course-Builder and My-Moodle) with the SeisTutor, on the basis of the strongly satisfactory level on a likert scale of 1 to 5 ranging from strongly dissatisfied to strongly satisfy.

GUI Based

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of learner with SeisTutor, is only 16%, while with the My-Moodle, this percentage increases to 24%. The Neutral level of learner with SeisTutor, is 21%, while with Teachable, this percentage increases to 43%. The Strongly Satisfaction level of learner with SeisTutor, is 71 %, while with My-Moodle, this percentage decreased to 46 %.

Learner Centric Learning Environment

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of the learner with the SeisTutor, is 12%, while with the Course Builder, this percentage increases to 84 %. The Neutral level of learner with SeisTutor, is 6%, while with the My-Moodle, this percentage increases to 17%. The Strongly Satisfaction level of learner with SeisTutor, is 82 %, while with the Course Builder and Teachable, this percentage decreased to 4%.

Dynamic Profiling

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of the learner with the SeisTutor, is 10 %, while with the Teachable, this percentage increases to 68%. The Neutral level of the learner with the SeisTutor, is 7%, while with the My-Moodle, this percentage increases to 18%. The Strongly Satisfaction level of the learner with the SeisTutor, is 83 %, while with the Teachable, this percentage decreased to 23 %.

Learning Content

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of the learner with the SeisTutor, is 17 %, while with the Teachable, this percentage increases to 93%. The Neutral level of the learner with the SeisTutor, is 5 %, while with the My-Moodle, this percentage increases to 36%. The Strongly Satisfaction level of the learner with the SeisTutor, is 78 %, while with the Teachable this percentage decreased to 3 %.

Resolving Query during Session

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of the learner with the SeisTutor, is 23 %, while with the Course Builder, this percentage increases to 63%. The Neutral level of the learner with the SeisTutor, is 9 %, while with the My-Moodle, this percentage increases to 13%. The Strongly Satisfaction level of the learner with the SeisTutor, is 68 %, while with the Course Builder this percentage decreased to 28 %.

Navigation Support

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of the learner with the SeisTutor, is 20 %, while with the Course Builder, this percentage increases to 39%. The Neutral level of the learner with the SeisTutor, is 12 %, while with the My-Moodle, this percentage increases to 27%. The Strongly Satisfaction level of the learner with the SeisTutor, is 68 %, while with the Course Builder this percentage decreased to 50 %.

Learner Feedback.

From the analysis, it has been concluded that the Strongly Dis-satisfaction level of the learner with the SeisTutor, is 14 %, while with the Course Builder, this percentage increases to 39%. The Neutral level of the learner with the SeisTutor, is 21 %, with the Teachable, this percentage decreases to 10%. The Strongly Satisfaction level of the learner with the SeisTutor, is 65 %, while with the Course Builder this percentage decreased to 46 %.

The conclusion drawn from this analysis is that all the tutoring systems mentioned above are lacking adaptivity, dynamic profiling, and personalization features. The critical feature of SeisTutor is personalization, adaptivity and dynamic profiling. From the comparative analysis, it has been observed that 71 % of learners are strongly satisfied with the GUI based feature, 82 % with Learning Centric Learning Environment feature, 83 % with Dynamic Profiling feature, 78 % with Learning Content feature, 68 % with Resolving query during session feature, 68 % with Navigation Support feature and 65 % with Learner feedback feature. The overall conclusion from the comparative study is that the satisfaction level of learners with the SeisTutor is 74%, with My-Moodle is 40.36 %, with Teachable is 35.43 % and with Course Builder is 30.92%.

Chapter 8 Conclusion and Future Scope

This chapter summarizes the work conducted in this research. The summary of the contribution of the conducted research has been underlined. Subsequently, the conclusions and the future scope in this area based on the conducted research have been described.

8.1 Summary

The objective of the current research work is to develop an adaptive tutoring engine, facilitating, knowledge base delivery through a learner-centric learning path. The design and development of an adaptive domain model and pedagogy model make the tutoring engine, an adaptive tutoring engine and provides the learner-centric learning path to the learner. For the current scope of work, the domain knowledge incorporated in ITS is Seismic data interpretation, which is an experiential knowledge domain. Thus, acquiring, characterizing, sequencing, validating, and developing personalized course content (based on learner's learning profile and learning style), of the SDI knowledge domain creates a pool of adaptive knowledge base or repository. The adaptive pedagogy model leads to the systems that provide Custom-Tailored Learning material to the learner based on the learner's prior knowledge, learning profile, and learning style. The Custom-Tailored Learning Path recommendation at the beginning of the learning session is rarely recommended in the existing ITS, this is due to the lack of empathy in ITS. Thus, this research aims to focus on the domain model and the pedagogy model. Therefore, the answer of the research questions is discussed below. The research questions drawn from the literature are–What are the steps involved to gather experiential knowledge from domain experts? How to represent experiential knowledge? On what criteria, learning material is aligned as per learner preference? How to generate a course coverage plan, which is exclusively designed for the learner? How a system can identify the learner preferences, exclusive course coverage plan, and give a custom-tailored pedagogical recommendation for adaptivity?

The following highlights the research contribution based on the conducted research work.

- An adaptive domain model indicates that the ITS offers an adaptive learning material that is offered as per the instruction received from the pedagogy model. Adaptive learning material specifies that the learning materials are aligned or structured as per the learner competency level and the learning preferences. As mentioned above, the seismic data interpretation domain is highly individualistic. Therefore, for gathering causal maps and semi-structured acquisition techniques are utilized. After extraction of knowledge, Knowledge manager sequences and classify the gathered knowledge as per seismologist's guidelines. The knowledge manager then validates the sequenced knowledge through ongoing consultation with seismologists and develops knowledge Capsules. To make the adaptive domain model, the learning materials and restructured and realigned as per learning profile ('Beginner', 'Intermediate', 'Expert') and learning style ('Imagistic', 'Intuitive', 'Auditory', 'Active') adding up to twelve different combinations. Therefore, the tutoring engine offering the learner a customized learning experience by delivering tailored subject matter.

- An adaptive pedagogy model indicates that ITS offers a Learner-Centric learning path. The Learner-Centric Learning Path specifies that ITS offer personalized learning paths. This intelligent feature is implemented using the "BUG MODEL". The BUG MODEL is used to identify the learner's previous/prior knowledge by identifying the learner's bugs during the pretest. The proposed novel approach has the advantage to determine the learner prior-knowledge and recommends the custom-tailored course coverage plan that improves the effectiveness of the system.

8.2 Conclusion

This research work focused on the development of a personalized, intelligent tutoring system for the domain "Seismic Data Interpretation". This research work illustrates the design, development and evaluation of the personalized intelligent tutoring system. The proposed personalized intelligent tutoring system christened as SeisTutor, emulates the human cognitive intelligence by incorporating the artificial intelligence features, i.e. Custom-Tailored Curriculum Sequencing Module, Tutoring Strategy Recommendation module, CNN based Emotion Recognition Module and Performance Analyser Module (Degree of Understanding Module). Total 60 learners have participated in the evaluation process. The participants were classified into two groups: Control Group and Experimental Group. Out of 60 participants, 32 of them designated as Control Group, and remaining 28 is designated as Experimental Group.

There are two aspects of the evaluation process, the first aspect is to identify which group prompts improvement in learning and second aspects is to determine the learner's behavior, reaction, comfort level and overall results. The First aspect of the evaluation process is accomplished by using the one-Tailed ANOVA and Second aspect of the evaluation process is accomplished by using well accepted four phases/ stage Kirkpatrick evaluation model.

ANOVA tests conducted on the pretest and posttest scores. The results indicate the effective learning gain of 44.34 % by Experimental group. The calculated F ratio of the ANOVA test for the experimental group is 119.71, which is higher than the calculated F ratio for control group 21.68. Thus, the Experimental group is having a significant difference in the posttest and pretest scores and provides effective learning against the control group.

Kirkpatrick's Four Levels Evaluation Model is another widely accepted method for evaluating the effectiveness of the learning program. The levels are 1-Reaction, 2-Learning, 3-Behavior, and 4-Results. The outcome of reaction reveals that 44 % of learners are happy with the offered learning content (customized learning content) and teaching process, i.e. pedagogy. The outcome of learning reveals that, experimental group possesses 44.34 % of learning gain and control group holds only 24.8%. Thus, the experimental group succeeds in enhancing the learner interest and curiosity, which indirectly increases the learner's performance. The outcome of behaviour reveals that the proposed system design produces productive learning in Seismic Data Interpretation through incorporating computer science and artificial intelligence features. Besides, 86% of learners were satisfied and achieved better results with SeisTutor and improved their learning with the selection of appropriate Adaptive Tutoring Strategies. The outcome of the results indicates that calculated T value ($T_{Stats},$) for the experimental group is 11.410 and control group is 5.312, P<0.01. The average posttest score of Experimental group was 2.21786 points which are higher than pretest scores. The average posttest score of Control group was 1.24719 points which are higher than pretest scores. Here the calculated($T_{Stats},$) is greater than $T_{critical}$, thus both the groups rejected hypothesis 1.0 and 2.0. Furthermore, the T_{Stats} value of both the groups are compared. From the results it has been revealed that the Experimental group provide more effective learning against Control group. In addition to this SeisTutor is compared with the existing open source tutoring system. From the analysis, it has been concluded that 74 % of learner are strongly satisfied with the SeisTutor ('*GUI based*', '*Learner-Centric Learning Environment*', '*Dynamic Profile*', '*Learning Content*', '*Resolving Learner Query during Session*', '*Navigation Support*', and '*Learner Feedback*').

8.3 Future Scope

The findings of the developed system in this thesis can be used for further research and development. In the accompanying sections, conceivable future headings are discussed.

Through the findings and discussion of the study's recommendation and future scope have been put forward, these are as follows.

- In the future, the implementation of a domain-independent intelligent tutoring system will be a new sub-domain to be explored. The domain independence reduces the efforts of creating a whole ITS system.

- Extension of Custom-Tailored Curriculum recommendation in the tutoring system will be the area to be worked on. There is a need to find out other intelligence techniques for determining learner's lack of knowledge of technical terms, which is discussed during the ongoing learning session. Currently, the Custom-Tailored Curriculum module recommends the Learner-Centric learning path based on the prior knowledge of the learner at the beginning of the learning session.

- In this research work, the CNN based emotion recognition module is used to track the learner's emotion during the ongoing learning session. In the future, facial expression can be considered as a key parameter for pedagogy flipping (when the learner is not happy with the recommended pedagogy) during the ongoing learning session.

- This research work considers only twelve Tutoring Strategy (the combination of one Learning style with the one Learning profile). In the future, the combination of more than one learning style with one learning profile can be considered for ITS.

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