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Research paper

A new student model for an intelligent tutoring system using analytical hierarchy process

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Abstract

Understanding student's thinking ability, strengths, weaknesses, learning behavior and their learning capacity are essential considerations in the virtual learning environment (VLE). The prime objective of this research study is to design a 'Student Model' based on individual's 'bio-psychological potential'. Defining a student model is crucial for an Intelligent Tutoring System (ITS) to adapt to the needs and knowledge of an individual student. Psychometric Assessments were used as diagnostic tools to understand student's cognitive and personality traits. These assessments have to fulfill three major criteria, which are standardization, reliability and Validity. The first phase of this research study focuses on the primary data compilation using psychometric assessments, to categorize the cognitive traits and personality traits of the individual. A sample size of 1145 was gathered from 22 engineering colleges of South Indian states. Primary data are collected by administering suitable psychometric inventories such as Benziger Thinking Style Assessment (BTSA) for Brain Dominance Analysis, Kolb's Learning Style Inventory (LSI) for the learning style identification, Howard Gardner's MI inventory for multiple intelligence identification and Paul Costa R. Robert McCrae's Big Five personality identification. This study consists of three major components namely, Personalized Profiling System (PPS), Mean-Difference clustering algorithm and the Analytical Hierarchy Process (AHP) algorithm. The study evaluates the performance of PPS through a feedback mechanism. Due to subjective nature of this process, the achieved accuracy is about 70%. The best decision is done based on the priorities provided by the AHP decision maker.

Keywords: *Analytical Hierarchy Process (AHP); Intelligent Tutoring System; Thinking Style; Learning Style; Multiple Intelligence; Psychometric Assessment.*

1. Introduction

In the Recent days, Information Communication and Technology (ICT) are playing a major role in teaching learning process. In the virtual education environment, understanding a student's strength, weakness, learning capacity, grasping skills, logical skills, mathematical skills, language skills and attitude is quite challenging. Educational research have unlimited opportunities to select and apply technology in numerous ways that connect with the interests of their students to achieve their learning goals. Several educational research studies have developed the systems to differentiate individuals based on learning activities, knowledge level and behavior in the virtual learning environment [1].

Modeling a student's learning behavior is one of the essential component of an Intelligent Tutoring System - ITS [2-3]. It provides an understanding of needs and knowledge levels of an individual student. Personalized systems are used in designing: learning environment, learning flow, content flow and collaborative environment for problem solving, learning activities, learning assessment, learning evaluation, feedback system.

The initial phase of this research study focuses on primary data compilation using psychometric assessments, in order to distinguish the cognitive traits and the personality traits of every individual. The student's individual strength, weakness, interests and the learning approaches were analyzed based on Benziger Thinking Style Assessment (BTSA) [4] & [5] and Kolb's Learning Style Inventory (LSI) [6]. Every individual's expertise in eight intelligence components were identified using Howard Gardner's Multiple Intelligence Assessment theory [7]. The foremost big-five personality assessment of an individual's behavior patterns were identified through Paul Costa R. Robert McCrae's method [8]. The standardization, reliability and validity of these 4 theories are shown in the Table 1.

Table 1: Standardization, Reliability and Validity of Four Theories

Inventory Name	Standard-ization	Validity	Reliability	Number of Research Papers	Empirical Research
Thinking Style Assessment	Yes	More than 10,000 people were scanned over ten years through MRI and PET	More Stable	4	Yes
Learning Style Identification	Yes	More	Relatively Stable	More than 1600	Yes
Multiple Intelligence Identification	Yes	Lesser	Relatively Stable	More Influential in school education	MI often called as 'Pseudoscience' due to its lack of empirical research evidences
Big Five personality Assessment	Yes	Moderate	Moderately Stable	More than 2600	The BIG-Five model is acquired the status of a reference model for trait research.

Rule-based classification technique is used to understand the individual's innate capacity (Model-1 Datasets) and their holistic developmental characteristics (Model-2 Datasets). From these two models the Personalized Profiling System (PPS) is built to generate the psychometric profile for the individual. Subsequently feedback was collected in order to verify the system robustness. PPS can be treated as a 'student model' of the Virtual Learning Environment (VLE).Clustering technique is used to differentiate the diversified group of students into four different categories. Mean-difference clustering method was proposed to customize the personalized education. Personalized education methods are suggested for all the four groups of students.

Finally, the framework model is proposed for an Intelligent Tutoring System (ITS) in order to provide a personalized education methodology, considering individual's thinking style, learning style, multiple intelligences and personality traits. The proposed 'Student Model' consists of Personalized Profiling System (PPS), Mean-Difference clustering method and the outcome of Analytical Hierarchical Process (AHP). A major constituent of this research study includes educational technology, educational psychology, clustering techniques and multiple criteria decision making method. The work flow diagram is shown in the Fig 1.

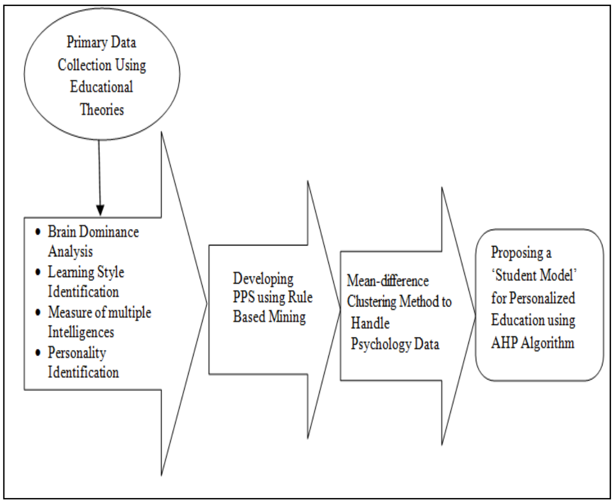

Fig. 1: Research Framework.

a) Brain Dominance Theories

Benziger Thinking Styles Assessment (BTSA), which is a powerful state-of-the-art tool, has proven to be highly effective in a wide range of areas, in assisting people to improve their self-management skills, general effectiveness and collaborative capabilities [9].

Broadly, the brain dominance is classified as right brain dominant (intuitive, thoughtful, and subjective) or left brain dominant (logical, analytical, and objective). In this study a detailed classification result has indicated that 8 kinds of dominances could be used for understanding the personality, as shown in Table III.

Benziger assumed that some people develop a particular combination of dominance modes (single, dual brained, triple brained and whole brained). Similarly, the double rights categories are characterized by the 'intuitive' and 'feeling' as predominant functions. The double lefts show predominant 'thinking' and 'sensing' functions. This study recommends investigating the dominance analysis for the larger samples in the academic context [10].

b) Learning Style Preferences

The commercial industries and academics were extremely influenced to use Kolb's Learning Style Inventory (LSI) due to its validity, reliability, stability and practical applications. LSI inventory is developed based on the results and conclusions of the three domains namely, psychology, philosophy and physiology [11].

The learning stages and learning cycle are to be used by teachers to critically evaluate the learning provisions. Educators should ensure that best suiting learning activities be designed and implemented to engage a learner [12].

The importance of investigating the complex relationships among abilities, learning styles, cognitive styles, and interests are essential. Ability refers to performing certain cognitive tasks like language proficiency, mathematical problem solving, aptitude and subject knowledge. Individual's show a learning tendencies to develop on their strengths and abilities based on their selected learning styles. To some extent, students tend to prefer learning styles that are well-suited to their leading intelligence [13].

Students prefer learning materials that are compatible with their learning styles and abilities. In this study, it was pointed out that mismatches are the root cause of learning difficulties. This study also shows that highly successful students have multi-style preferences [14].

Following are the four learning styles

1) Concrete Experience (CE)
2) Reflective Observation (RO)
3) Abstract Conceptualization (AC)
4) Active Experimentation (AE)

c) Multiple Intelligence Theory

Howard Gardner points out that most of the educational approaches give importance only for logic-mathematical and verbal-linguistics intelligences. Relating MI theory to individuals learning style is an interesting notion because, learners expand their knowledge base by linking new information.

Following are the eight kinds of intelligences identified by A.J. Gardner

1) Visual-Spatial (VSI)
2) Bodily- Kinesthetic (BKI)
3) Musical (MUI)
4) Interpersonal (II-1)
5) Intrapersonal (II-2)
6) Linguistic (LI)
7) Logical –Mathematical (LMI)
8) Naturalistic (NI)

d) Big Five Personalities

The Big 5 personality traits indicate that, notably the conscientiousness, extraversion and neuroticism have a significant impact on the education achievement. Based on the findings of this research, it is proven that the Big 5 personality traits indeed have a significant relationship with the student performance, both positively and negatively. Multiple linear regression analysis of this research shows that 48.04% student performance is affected by the traits [15 & 16].

Following are the five personality traits.

1) Extroversion (F1)

2) Neuroticism (F2)
3) Conscientiousness (F3)
4) Agreeableness (F4)
5) Openness to experience (F5)

The paper discusses about research methodology, primary dataset description, statistical measures and applied data mining techniques that are used in descriptive and predictive analysis. Rule-based classification technique is used to understand the individual's innate ability (Model-1 Datasets) and their holistic characteristics (Model-2 Datasets). Using these two data models the Personalized Profiling System (PPS) is built. PPS generates the psychometric profile to describe an individual in a self-referential method.

The following research methodology will bridge the gap between educational psychology and the educational technology.

1) Psychology data collection
2) Data pre-processing
3) Data transformation using rule based mining method
4) Data modeling
5) Building a Personal Profiling System (PPS) using rule based mining.
6) PPS robustness verification
7) Mean Difference Clustering Method
8) Multiple criteria decision making method using Analytical Hierarchy process (AHP) algorithm.

Finally, a Framework model is proposed for building an Intelligent Tutoring System (ITS) in order to provide a personalized education considering individual's thinking style, learning style, multiple intelligences and personality traits.

II. Data Collection

A short personalized letter was sent in advance to collect the primary data. 22 colleges have responded positively. A free talk was given on 'Principles of Learning Sciences and Psychometric Assessments'. Native language translation is also provided to support the native speakers for the effective participation. Sufficient amount of instructional page and navigation paths are provided.

2. Pre-processing

Traditional survey methods as well as e-survey methods were used in primary data collection. The survey typology is shown in the Table 2 (Annexure). Data are collected into CSV file format. In the phase of pre-processing, the missing or incomplete data records are eliminated.

Table 2: Survey Topology

Face-To-Face	Typology Of Survey	Advantages	Disadvantages
	Traditional Use Of Material – Paper Based Survey Using 'Printed Booklets' Number Of Samples – 845 E-Survey Number Of Samples – 300	Time Consuming And Easy Calculation	Manual Data Entry, Expensive
Computer - Assisted	Digital Questionnaire Design And Planning Considerations Notepad Is Used For Creating The Questionnaire. GIFT Format Is Used To Upload The File Into LMS An Open Source Educational Software Named Modular Object Oriented Dynamic Learning Environment (MOODLE)	Cost Effective	Additional Efforts Are Taken In Developing The Software For The Data Collation. Using JDK 1.1 - HSSF Apache POI Packages And Net Beans 7.4 IDE

3. Data modeling

Rule based classification method is used for data modeling. The transformed data models are named as, Model-1 and Model-2. Data classification is done using four psychometric data sets namely, thinking style, learning styles, multiple intelligences, and personality types. These two data models are used in developing Personal Profiling System (PPS).

a) Model- 1 Data

The classification is done based on the leading characteristics or predominant traits of the participants in each inventory. $\mu 1$, $\mu 2$, $\mu 3$ and $\mu 4$ are calculated for each candidate using a set of questionnaire. Table III shows the list of rules used in brain dominance analysis based on the leading preferences.

Table 3: BD Labels and its Interpretation

Leading Brain Dominance
Basal Left High(BLH): If (μ_1>(μ_2 and μ_3 and μ_4 and 15))
Basal Right High (BRH): If (μ_2>(μ_1 and μ_3 and μ_4 and 15))
Frontal Right High (FRH): If (μ_3>(μ_1 and μ_2 and μ_4 and 15))
Frontal Left High (FLH): If (μ_4>(μ_1 and μ_2 and μ_3 and 15))
Basal Left Low (BLL): If (μ_1>(μ_2 and μ_3 and μ_4 and <=15))
Basal Right Low (BRL): If (μ_2>(μ_1 and μ_3 and μ_4 and <=15))
Frontal Right Low (FRL): If (μ_3>(μ_1 and μ_2 and μ_4 and <=15))
Frontal Left Low (FLL): If (μ_4>(μ_1 and μ_2 and μ_3 and <=15))

Table IV below shows the sample result of classification for brain dominance.

Table 4: Sample Result of Classification for BD

Cid	Btsa Score				Brain (Bd)	Dominance
	μ_1	μ_2	μ_3	μ_4		
C1	17	19	16	15	Brh	
C10	18	17	12	18	Blh	
C11	11	9	13	7	Frh	
C12	7	11	9	13	Flh	

For example the candidate C10 having BLH type BD can be interpreted as follows. 'BLH' is disciplined and ordered in nature and will follow the instructions and will meet his/her deadlines. He or She is reliable but highly dependable on the instructions of the higher authorities. He or she prefers working in a sequential order and doesn't encourage multitasking or pipelined activities. His/her working style is bureaucratic and behaves diplomatically. He/she is more interested in having an organized and detail plan or activity. He/she rely on written communication to oral communication. Finally, he/she does the assigned task systematically and accurately.

Below Table V shows the sample classification results of learning style identification.

Table 5: Learning Style Classification Results

Cid	Kolb				X	Y	Lsi
	Ce	Ro	Ac	Ae	Ae-Ro	Ac-Ce	
C1	10	18	17	13	-5	7	Ae
C10	19	20	13	10	-10	-6	Ce
C11	19	12	17	15	3	-2	Ro
C12	12	14	18	18	4	6	Ac

The results of multiple intelligences are shown in the below sample Table VI. Every person has different types of intelligences at various scales. However we are interested in only top 2 intelligences based on their scores. The candidate can be advised / groomed based on his primary two skills.

Table 6: Identification of Prime Two Results P1 and P2

Cid	Multiple Intelligence								P-1	P-2
	Li	Lmi	Mui	Bki	Vsi	Ii1	Ii2	Ni		
C1	34	37	35	25	32	34	35	36	Lmi	Li
C10	34	33	38	30	28	31	37	34	Mui	Lmi

C11	27	24	27	26	24	25	29	36	Ni	Lmi
C12	33	33	26	31	32	33	35	26	Ii2	Ni
C13	36	34	33	33	32	32	32	27	Li	Ii2
C14	27	29	33	28	35	32	27	34	Vsi	Li
C15	32	25	39	30	32	32	29	33	Mui	Li
C16	30	32	31	29	32	35	30	31	Ii1	Ii2

Below Table VII shows the set of rules, class labels and interpretations used in BIG-Five personality assessment.

Table 7: Big 5 Class Labels and Their Interpretations

Personality Notations and its interpretations
If (F1 < 20) then N1 is "S" else "R";
If (F2 < 20) then N2 is "C" else "L";
If (F3 < 20) then N3 is "O" else "U";
If (F4 < 20) then N4 is "A" else "E";
If (F5 < 20) then N5 is "I" else "N";

Table VIII shows a sample classification result of Big 5 personalities. For example the participant C10 is of type SCOAI. It indicates 'Social', 'Calm', 'Orderly', 'Accommodating', 'Inquisitive'. On the basis of personality analysis, participant C10 is strongly 'Social'.

b) Model- 2 Data

The classification is done based on the competency level and holistic approach of an each individual. Table IX discusses about the various labels involved in the brain dominance analysis. 16 different class labels are used in the brain dominance analysis. Katherine Benziger stated that worldwide 5% of people only possess WBD. In current study also, similar results were found. Only 4.4% of the samples belonged to WBD.

Below Table X shows the set of rules used in classification and their interpretations.

Table XI shows the scores of participants on the 16 types of BDs out of a sample of size 1145.

For example the participant 'C127' belongs to Whole Brain Dominance (WBD) and noticeably all the four modes having the scores more than '15'. These personalities are capable to excel in any field as well as they possess leadership quality and be able to manage larger size of projects and manpower likewise, the participant 'C1009' belongs to PBD and noticeably all the four modes having scores less than '15'. Poor Brain Dominance (PBD) personalities are prone to have 'Prolonged Adaptation Stress Syndrome (PASS)' when they handle challenging tasks.Table XII shows the set of rules, labels and its interpretations used in the multiple intelligence analysis. Humans have different types of dominant intelligences, and each individual's intelligence consists of different combinations of intelligences in certain levels. The higher competency level is associated with the M1 and the lower level is shown by M5. Out of eight intelligences, M6 is mixed with the extremely well performed and extremely poor performed.

Table XIII shows a sample result of MI classification. Understanding about individuals in leading intelligence provides the direction to exemplify the skills of an individual' as well as provide the avenue to understand about the lack/grey area of an individual. For instance, the participant 'C1002' is inclined towards 'Inter-Personal Intelligence-(II1)' and 'Naturalistic Intelligence-NI'.

Following are the classes/labels and its interpretations used in BIG-Five analysis.

Following are the classes/labels and its interpretations used in BIG-Five analysis.

P1: SCOA, P2: RCOAI, P3: SCOAN, P4: SCO, P5: COA, P6: OAI, P7: SC, P8: CO, P9: OA, P10: AI, P11: SI, P12: RI, P13: S, P14: LUEN and Table VIII has already shown the sample results of "BIG-Five" personality's classification.

Learners those who belong to the categories P1, P2, P6, P10, P11, P12 are 'Ambitious and Creative' whereas, the categories P7, P13, P14 are 'Gregarious and Impulsive'. The remaining are 'Dim and Ego-centric'. Several empirical researches have shown that individual's personality, attitudes and beliefs are more strongly associated with school performances and test scores.

Table XIV shows sample of the primary data sets as well as two different sets of transformed data namely Model-1 and Model-2. These two sets are used in developing the PPS. Using four psychometric inventories, 48 different labels are obtained using rule based data classification technique and it is named as Model-1 dataset. This dataset signifies individual's innate tendencies. Subsequently, in Model-2 dataset 40 different labels are obtained using rule based data classification technique. Model-2 dataset signifies individual's competency level and holistic study.

Table 8: Big-Five Personality Type Classification Result

Cid	Factor					Labels					Personality Type	Big -Five
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5		
C1	18	17	14	13	18	*S*	*C*	*O*	*A*	*I*	Scoai	P1
C2	16	23	24	20	21	*S*	*L*	*U*	*E*	*N*	Sluen	P13
C3	8	13	16	12	23	*S*	*C*	*O*	*A*	*N*	Scoan	P3
C4	18	23	16	18	16	*S*	*L*	*O*	*A*	*I*	Sloai	P6
C5	11	25	15	15	25	*S*	*L*	*O*	*A*	*N*	Sloan	P9

Table 9: Classes Used in Brain Dominance Analysis

Labels and Interpretations
WBD: Whole Brain Dominance is when the high score (>15) is found in all the four quadrants of the brain
TBD: Triple Brain Dominance is when the high score (>15) is found in any of the three quadrants.
For instance,
T1: (BL, BR and FR)
T2: (BR, FR and FL)
T3: (FR, FL and BL)
T4: (FL, BL and BR)
DBD: Double Brain Dominance is when the high score (>15) is found in any of the two quadrants.
For instance,
DB: Double Basal (BL and BR), DF: Double Frontal (FR and FL)
DR: Double Right (BR and FR), DL: Double Left (BL and FL)
SBD: Single Brain Dominance is when the high score (>15) is found in any one of the quadrant.
BL: Basal Left, BR: Basal Right, FR: Frontal Right, FL: Frontal Left
BPBD: Better than Poor Brain Dominance is identified with the score value is less than 15 and greater than 10 in all the quadrants.
PBD: Poor Brain Dominance is identified with the score value less than 10 in all the quadrants.
FBD: Falsified Brain Dominance is classifies the quadrants having high score are treated as Falsified Brain Dominance (BR and FL) and (BL and FR).

Table 10: Class Labels of Brain Dominance Analysis

Labels and Scores μ-Original Score for Each Brain Quadrant
Single Brain Dominance (SBD)
BL: If ((μ_1>μ_2 and μ_3 and μ_4) and ($\mu_1 \geq 15$));
BR: If (μ2>μ1 and μ3 and μ4 and (μ2 ≥ 15));
FR: If (μ3>μ1 and μ2 and μ4 and (μ3 ≥ 15));
FL: If (μ4>μ1 and μ2 and μ3 and (μ4 ≥ 15))
Double Brain Dominance (DBD)
DB: If ((μ1 and μ2)> (μ3 and μ4) and (μ1 and μ2) ≥ 15);
DR: If ((μ2 and μ3)> (μ1 and μ4) and (μ2 and μ3) ≥ 15);
DF: If ((μ3 and μ4)> (μ1 and μ2) and (μ3 and μ4) ≥ 15);
DL: If ((μ1 and μ4) > (μ2 and μ3) and (μ1 and μ4) ≥ 15)
Triple Brain Dominance (TBD)
T1: If (μ1 and μ2 and μ3) ≥ 15;
T2: If (μ2 and μ3 and μ4) ≥ 15;
T3: If (μ3 and μ4 and μ1) ≥ 15;
T4: If (μ1 and μ2 and μ4) ≥ 15
Whole Brain Dominance (WBD)
WBD: If the individual modes namely μ1 and μ2 and μ3 and μ4 are more than (≥) 15
Falsified Brain Dominance (FBD)
FBD: If ((μ1 and μ3) or (μ2 and μ4)) ≥15
Better than Poor Brain Dominance (BPBD)
BPBD: If ((μ_1 and μ_2 and μ_3 and μ_4) > =15 and < 10)
Otherwise Poor Brain Dominance (PBD)

Table 11: BTSA Scores and Labels

Sl. No.	Candidate ID	BTSA SCORE				LABELS
		μ_1	μ_2	μ_3	μ_4	
1	C1054	16	4	11	9	BL
2	C103	11	15	15	7	BPBD
3	C1037	3	16	9	12	BR
4	C146	19	16	7	13	DB
5	C230	14	13	17	17	DF
6	C166	16	13	8	17	DL
7	C101	14	16	16	14	DR
8	C363	12	16	11	18	FBD
9	C523	13	13	14	17	FL
10	C1026	7	8	17	8	FR
11	C1009	7	11	13	9	PBD
12	C1	17	19	16	15	T1
13	C138	13	16	17	15	T2
14	C126	19	14	15	16	T3
15	C10	18	17	12	18	T4
16	C127	17	18	19	17	WBD

Table 12: Class Labels Used in MI Analysis

Class Labels	Set of Rules	Interpretation
Note: The labelling priority starts from M1 to M6. At the end of every label creation records are filtered and the next label follows with the remaining records.		
M1	If the scores of all the eight intelligence's are above 30	Highly Advanced
M2	If the scores of all the eight intelligence's are above 25	Advanced
M3	If the scores of all the eight intelligences are above 20	Moderately Advanced
M4	If the scores of all the eight intelligences are above 15	Slightly Advanced
M6	If the scores of any five intelligences are above 15	Poor Level
M5	Otherwise	Mixed Level

Table 13: Multiple Intelligences Classification Result

CID	Multiple Intelligences								MI
	LI	LMI	MUI	BKI	VSI	II1	II2	NI	
C133	38	38	39	36	38	37	40	36	M1
C10	34	33	38	30	28	31	37	34	M2
C108	24	24	25	31	27	23	31	25	M3
C127	32	20	40	22	25	30	26	32	M4
C468	26	15	23	24	32	25	25	22	M5
C134	15	20	22	21	21	19	19	18	M6

Table 14: Data Set Description

Primary Dataset																					
Cid	Thinking Style				Learning Style				Multiple Intelligences								Big-Five Factors				
	μ_1	μ_2	μ_3	μ_4	Ce	Ro	Ac	Ae	Li	Lmi	Mui	Bki	Vi	Ii1	Ii2	Ni	F1	F2	F3	F4	F5
C1	17	19	16	15	10	18	17	13	34	37	35	25	32	34	35	36	6	10	15	13	9
C10	18	17	12	18	13	22	15	15	34	33	38	30	28	31	37	34	17	23	19	28	24
C100	17	17	17	13	15	17	15	14	27	24	27	26	24	25	29	36	18	17	14	13	18
C1000	11	9	13	7	19	20	13	10	33	33	26	31	32	33	35	26	24	26	8	17	26
C1001	12	8	13	7	13	17	14	18	36	34	33	33	32	32	32	27	16	16	12	12	24
Model-1 Dataset																					
Cid	Learning Style Preferences																				

	Leading Brain Dominance		First Leading Intelligence	Second Leading Intelligence	Big-Five Elements
C1	Br	Ae	Lmi	Li	Scoai
C10	Bl	Ae	Mi	Lmi	Sloen
C100	Bl	Ae	Ni	Lmi	Scoai
C1000	Fr	Ce	Ii2	Ni	Rloan
C1001	Fr	Ae	Li	Ii2	Scoan

Model-2 Dataset

Cid	Brain Dominance Type	Multiple Intelligence Competency Level	Big-Five Personality Labels
C1	T1	M2	P1
C10	Db	M2	P13
C100	T1	M3	P1
C1000	Pbd	M2	P9
C1001	Pbd	M2	P3

The Personal Profiling System (PPS) is developed using qualitative interpretations. The qualitative interpretations of few samples are explained in short as follows:

For instance the 'Candidate - C1' can be interpreted as follows

- Basal Right (BR) : The candidate feels highly centered, respects traditional values, ethical, seeks harmony and more intuitive
- Active Experimentation (AE) : The candidate is active in doing experimentations and seeks for evident learning
- Logical-Mathematical Intelligence (LMI) : The First Prime Intelligence (MI-I).
- Linguistic Intelligence (LI: The Second Prime Intelligence (MI-II):
- SCOAI signifies five attitudes per se Social (S), Emotionally Calm (C), Orderliness (O), Accommodative (A) and Inquisitive (I). In general this type of personality is more appreciated by both family and in professional life. This type of personality seems to be harmonious within themselves in all the circumstances. They tend to accept the challenges.

Table XV indicates that the Model-2 dataset has four attributes such as Brain Dominance (BD), Learning Style Identification (LSI), Multiple Intelligence (MI) and Big Five Personality Types (BIG-Five) respectively. This dataset is formed using rule based classification method. In this model, holistic approach is considered.

Table 15: Model-2 Dataset for Qualitative Interpretation

Candidate ID	BD	LSI	MI	BIG-Five
C1	T1	AE	M2	P1
C10	DB	AE	M2	P13
C1000	PBD	CE	M2	P9
C1002	PBD	RO	M3	P13
C105	BL	CE	M3	P14

The qualitative interpretations of few samples are discussed as follows:

For instance the 'Candidate - C105' can be interpreted as follows.

- Single Brain Dominance (BL: Difficult to work with additional type of work except their routine work, scared to take up challenges, lesser competent, resistant to admit new things and dynamic activities.
- Concrete Experiencing (CE): Seeks for concrete evidences to learn things, likes demonstrations and simulations, reduced imaginative power.
- Moderately Advanced (M3): Inadequate in all the eight intelligences.
- LUEN (P14) signifies four attitudes par Emotional Imbalanced (L), Unorganized (U), Egocentric (E) and Non-Curious (N). In general this personality type is more intricate to understand both family and official life. This type of personality seems to be dissonant within themselves in all the circumstances. He/she is not ready to accept the challenges.

The above inferences are obtained through observational, experiential and qualitative learning. Personal interrogation is carried out on around 600 candidates among the sample of n=1145 as well as feedback was collected through software from all the respondents' too. Feedback was used to verify this hypothetical study.

Rudimentary analysis is necessary to understand about the temperament, abilities and characteristics of the learners. The cross tabulation analysis is also essential for all the type of empirical analysis. The basic inferences are obtained in order to understand the highest count and lowest count between two different variables. 73 class labels were used in PPS. The complete profile of the candidate is generated based on psychometric assessment. Sensitive analysis was also carried out in order to understand the consistency and validity of PPS.

4. Cluster analysis

Several educational research studies have developed a system to differentiate individuals based on learning abilities and learning behavior in the virtual learning environment. However, there is a need for learner categorization into a smaller number of groups for designing an instructional intervention. Grouping students among different cognitive profile is a challenging task. In this section, investigation is done to differentiate the students into four categories amongst diversified combinations of individual's behavior.

The cluster formation algorithm is proposed to solve "the problem of learner categorization based on cognitive capacity". In the Model-2 statistical data analysis, Chi-Square results are shown (0.000, $p \leq 0.05$) significance value between the variables BD and MI, which infers the dependency association between these two variables. Hence, a bi-model theory with the combination of brain dominance analysis and multiple intelligences are aimed.

The instances of each class are not in the form of psychological interpretations and the instances of outliers are treated as different cluster. In addition to k-means algorithm, DBSCAN and Two-Step clustering techniques are attempted. However, the loss of interpretability erupts.

Therefore, mean-difference clustering method is proposed. Norm-referenced tests are designed to provide a measure of performance that is interpretable in terms of an individual's relative standing score/rank in some known group.

Mean difference value is considered for improving the classification accuracy within a particular group. Mean values are useful when creating groups or bins to organize large sets of data. Mean value is obtained by dividing the sum of the observed values of the number of instances. The mean-difference clustering method is shown in the steps below.

Input: Scores of Brain Dominance and Multiple Intelligences.

Output: Learner Categories: Excellent, Good, Average, Poor

Method:

1) Calculate the sum of four quadrant's score for each participant

$$SBD\ [1] = \sum_{1}^{1145} \mu_1[I] + \mu_2[I] + \mu_3[I] + \mu_4[I]$$

2) Calculate the sum of eight intelligence's score for each participant

$$SMI\ [1] = \sum_{I}^{1145} LI_I + LMI_I + MUI_I + BKI_I + VI_I + III1_I + II2_I + NI_I$$

3) Find the mean for SBD and SMI

$$\boxed{MBD = \frac{1}{1145}\sum_{I=1}^{1145} SBD\ [I]}$$

And

$$\boxed{MMI = \frac{1}{1145}\sum_{I=1}^{1145} SMI\ [I]}$$

4) Find the mean difference value for each participant

a) Bd_Difference[I] = Sbd[I] – Mbd

b) Mi_Difference [I] = Smi[I] – Mmi

5) ASAS: Four classes are obtained based on Rule-Based Classification
a) If ((BD_DIFFERENCE[I] ≥ 0) & (MI_DIFFERENCE[I] ≥ 0)) then it is labelled as "Excellent"
b) If ((BD_DIFFERENCE[I] > 0) & (MI_DIFFERENCE[I] < 0)) then it is labelled as "Good"
c) If((BD_DIFFERENCE[I] < 0) & (MI_DIFFERENCE[I] > 0)) then labelled as "Average"
d) If ((BD_DIFFERENCE[I] < 0) & (MI_DIFFERENCE[I] < 0)) then labelled as "Poor"
6) Find the minimum and maximum values of BD_DIFFERENCE [ ] to fix the X-axis.
7) Find the minimum and maximum values of MI_DIFFERENCE [ ] to fix the Y-axis. Visual plotting of BD_DIFFERENCE [I] and MI_DIFFERENCE[I].

The highlights of the clustering algorithm are:
1. Applicable for both of the genders
2) Provides best categorical analysis within the group
3) Outlier detection is made easy

The goodness of the mean-difference cluster algorithm and its characteristics are shown in the Table XVI.

Table 16: Experimental Results and Analysis

Attribute	Performance
Method	Partitioning and exclusive method
Accuracy	It predicts the class label correctly and the accuracy of the predictor is 100%
Time Complexity	Apriori time complexity of an algorithm is linear function O (N).
Robustness	Classifier make correct predictions up to 100%
Scalability	Withstands to construct the classifier or predictor efficiently given large amount of data.
Interpretability	Interpretation of the cluster results are made easy.
Validation	Fowlkes-Mallows Index (FM Index): The Fowlkes-Mallows index computes the similarity between the clusters returned by the clustering algorithm. The higher the value of the FM index, more similar clusters. It can be computed using the following formula. $FM = \sqrt{\frac{[TP]}{(TP+FP)} \times \frac{TP}{(TP-FN)}}$ (5.1) where, TP the number of true positives, FP is the number of false positives, and FN is the number of false negatives. The calculated FM index value for the MDCA algorithm is arrived as (5.1). Hence, the highest index value indicates the highest cluster validity.

Learner's categorization based on cognitive maturity is shown in the Table XVII. If both the variables DB_DIFFERENCE and MI_DIFFERENCE are positive then the instances are classified as 'Excellent' if both are negative, then the instances are classified as 'Poor' If BD_DIFFERENCE is positive and MI_DIFFERENCE is negative then instances are classified as 'Good' otherwise classified as 'Average'. For instance, the candidate 'C1007' have got negative scores in both of the variables, that is, -7 & -29, hence the competency level is classified as 'Poor'.

Table 17: Learners Categorization Based on Cognitive Maturity

Candidate ID	BD_DIFF	MI_DIFF	Competency Level
C1	20	32	Excellent
C100	17	-18	Good
C1000	-7	13	Average
C1002	-7	-37	Poor
C1007	-7	-29	Poor
C106	5	-35	Good
C1100	-7	-20	Poor

The demographic analysis of the cluster formation is shown in the Fig 2. Out of four categories the highest count is shown in "Poor" category, whereas the lowest count is shown in the "Good" category.

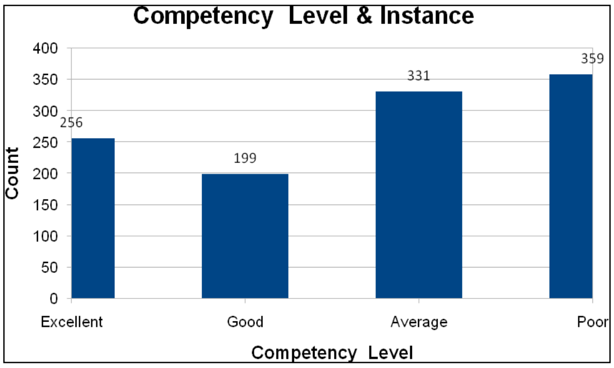

Fig. 2: Demographic Analysis Based on Competency Level

This dynamic visual map shows the cognitive profile based on Model-2 data classification. For instance, one of the learners 'C1' who appears in the 'Excellent' category is chosen to display in the cognitive profile. Table XVIII shows the cognitive profile based on Model-2 data augmenting the individuals' cognitive maturity.

Table 18: Cognitive Profile of the Participants

CID	BD	LSI	MI	BIG-Five	Competency Level
C1	T1	AE	M2	P1	Excellent
C10	DB	AE	M2	P13	Excellent
C100	T1	AE	M3	P1	Good
C1000	PBD	CE	M2	P9	Average
C1001	PBD	AE	M2	P3	Average
C1002	PBD	RO	M3	P13	Poor
C1009	PBD	AE	M2	P10	Poor
C101	DR	AE	M2	P7	Excellent

5. Multiple criteria decision making algorithm

This section discuss about multiple decision making algorithm and proposed framework model for the virtual education. AHP method is identified to handle multiple conflicting and subjective criteria [17]. The primary dataset consists of scores of thinking style, learning style, multiple intelligences and big five personality. In order to identify the best profile among the respondents the scores obtained in thinking style and multiple intelligences should be higher on the other hand the scores of big five factors should be lower. It is a conflicting criterion's inclusive of both minimization and maximization functions. Analytic Hierarchical Process (AHP) is a method used for organizing and analyzing multiple parameters in a decision making situations. This method is efficient for ranking the records based on set of alternatives.

a) Analytical Hierarchy Process (AHP)

The AHP is one of the effective methods among all other multiple-criteria decision-making. This methodology is capable of breaking down a complex, unstructured situation into its component parts. Subsequently these parts are arranged into a hierarchy order. Because of the uncertainty, vagueness and imprecision of human decision making AHP is used to evaluate the students based on their psychometric scores. The outcome ranking order of an AHP can be used to adopt teaching methodologies, personalized learning path, learning activities, learning assessment, student tracking method and on-line mentoring systems etc.

Though there is an increase in variety and complexity of e-learning tools still there is a gap exists to identify the student's cognitive strength and weakness. Decision support system is considered as a solution to optimization problem [18].

The analytic hierarchy is structured by the scores of brain dominance (number of parameters 4), multiple intelligences number of parameters 8) and Big-Five personality (number of parameters 5). Altogether 17 parameters are considered in the hierarchy analysis. In order to specify the pair wise comparison matrix, N (N-1)/2 pairs of criteria/sub-criteria/alternatives are evaluated. Assigning numeric values from 1 to 9 for the subjective judgment is based on the criterion characteristics and priority. The decision model for the 17 parameters is shown in the Table XIX.

In the multiple criteria decision making both minimization and maximization functions are allowed. The psychology dataset used in this research utilizes max function for thinking style (4 attributes) and multiple intelligences (8 attributes) and min function for the big five personality (5 attributes). The hierarchical scores for each parameter are shown in the Table XX.

The Eigen vector corresponding to the maximum Eigen value (λMax) is computed to determine the weight vectors of the sub-criteria. The normalized principle Eigen vector is shown in the Table XXI.

The final step of AHP is sensitivity analysis. This analysis is useful in providing the information related to robustness of decision making process. It is necessary to explore the impact of alternative priority structure for the rating of students based on cognitive traits and personality traits.

Compute the consistency index CI= (λ-n)/ (n-1)

Compute the random index RI = 1.98 (n-2)/n

Compute the consistency ratio = CI/RI

Accept the matrix if CR is less than 0.10

The obtained value for the consistency ratio is less than 10% (0.094444). This indicates that the subjective evaluation is consistent. The overall composite weight of each alternative choice is based on the weight of level 1 to level 17. The composite weight and rank in the ascending order for each candidate is shown in the Table XXII.

Table 19: AHP Decision Model

Attributes	BL	BR	FR	FL	LI	LMI	MI	VSI	BI	INTER	INTRA	NI	F1	F2	F3	F4	F5
Bl	1	1	0.2	0.5	0.5	0.5	1	1	1	0.34	0.34	3	3	3	3	3	3
Br	1	1	1	0.34	1	1	1	1	1	1	1	3	3	3	3	3	3
Fr	5	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3
Fl	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Li	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Lmi	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Mi	1	1	1	1	1	1	1	0.34	0.34	0.34	0.34	1	0.34	0.34	0.34	0.34	0.34
Vsi	1	1	1	1	1	1	3	1	3	0.34	0.34	3	3	3	3	3	3
Bi	1	1	1	1	1	1	3	0.34	1	0.34	0.34	3	3	3	3	3	3
Inter	3	1	1	1	1	1	3	3	3	1	3	5	1	5	5	5	5
Intra	3	1	0.34	1	1	1	3	3	3	0.34	1	5	5	5	5	5	5
Ni	0.34	0.34	0.34	1	1	1	1	0.34	0.34	0.2	0.2	1	1	1	1	1	1
F1	0.34	0.34	0.34	1	1	1	3	0.34	0.34	1	0.2	1	1	1	1	1	1
F2	0.34	0.34	0.34	1	1	1	3	0.34	0.34	0.2	0.2	1	1	1	1	1	1
F3	0.34	0.34	0.34	1	1	1	3	0.34	0.34	0.2	0.2	1	1	1	1	1	1
F4	0.34	0.34	0.34	1	1	1	3	0.34	0.34	0.2	0.2	1	1	1	1	1	1
F5	0.34	0.34	0.34	1	1	1	3	0.34	0.34	0.2	0.2	1	1	1	1	1	1

Table 20: The Hierarchical Scores

Category		Priority	Rank	Category		Priority	Rank
1	BL	5.60%	10	10	INTER	12.50%	1
2	BR	7.30%	5	11	INTRA	11.30%	2
3	FR	10.20%	3	12	NI	3.30%	17
4	FL	7.00%	6	13	F1	4.30%	11
5	LI	6.20%	8	14	F2	3.70%	13
6	LMI	6.20%	8	15	F3	3.70%	13
7	MI	3.90%	12	16	F4	3.90%	16
8	VSI	7.90%	4	17	F5	4.10%	14
9	BI	6.80%	7				

Table21: Composite Weight and Rank Order

Candidate ID	Composite Weight	Rank
Higher Ranks		
C16	0.911707	1
C2	0.892428	2
C133	0.891899	3
C339	0.884429	4
C265	0.881052	5
Lower Ranks		
C935	0.494005	1141
C1139	0.493542	1142
C399	0.486713	1143
C383	0.482217	1144
C638	0.468263	1145

If the student composite weight is higher naturally they can cope up with any type of learning activities and instructional methods. Personalized education and mentoring support is specially required for the student's those who have got lower ranks. Higher the rank better the academic performances can be expected. Lower the rank at time these students may struggle to cope up with few subjects.

6. Proposed framework model for an its

The major advantage of ITS is to provide one-to-one tutoring that cannot be achieved through human tutors for economic and social reasons. The central part of ITS research is the intersection of three main areas such as, cognitive psychology, computer science and educational research. This research provides the design and development strategies for the 'Student Model' of an ITS. Intelligent tutoring system cannot exist without an understanding of the student's needs, interest, learning style, capability and their knowledge. The entire model is developed with extensive theories of cognitive psychology. The overall framework architecture is proposed based on the research studies [19, 20, & 21]. The pedagogical activities are the outcome of an expert system as a series of deductions. The overall framework architecture is shown in the Fig 3.

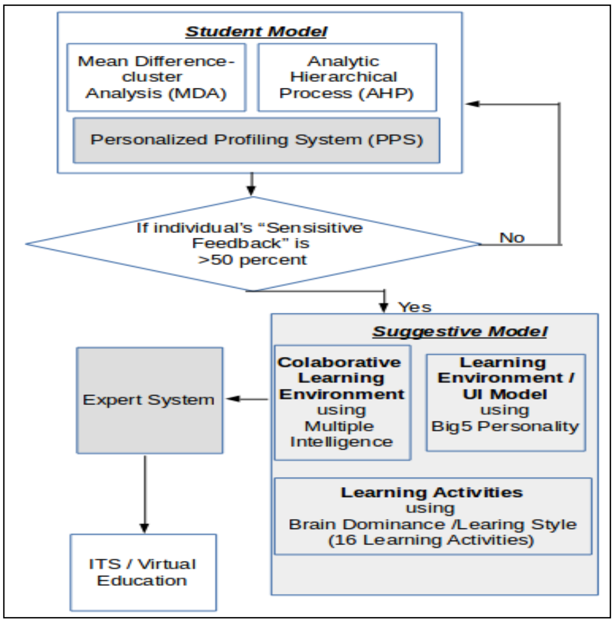

Fig. 3: Proposed Framework Models for Virtual Education.

Piaget believed that all children try to strike a balance between the learning stages of assimilation and accommodation [22]. Gagne has identified five major categories of learning such as verbal information, intellectual skills, cognitive strategies, motor skills and attitudes. Different internal and external conditions are necessary for an each type of learning [23]. Each learner seeks for the best material to be presented suitable to their learning style.
There are 12 different learning tools are recommended to incorporate in the virtual learning environment. The learning tools are 1) social communities, 2) online chats, 3) face-to face meetings, 4) mobile phone view, 5) forums, 6) text processing tools, 7) instant messenger tools, 8) e-mail, 9) integrated interactions, 10) bookmarking tools, 11) online groups, and 12) resource sharing tools. Each individual differ in their personality or behavior hence, the preference of learning tools may vary from each one.
For the collaborative learning activities the team is to build based on expertise in different intelligences. So that, each individual can share and develop their intelligence quotient from the peer group.
Proposed student model can be used for the following virtual learning activities: (1) building a recommender agent for on-line learning activities and shortcuts, (2) automatic guidance for the learner's and intelligent generation of learning objects, (3) determining the type of learning materials most suitable to be recommended, (4) identifying attributes characterizing the patterns of performance between various groups of students, (5) discovering interesting relationship between student's usage information, academic performance and psychometric patterns, (6) finding the relationship between each pattern of learner's behaviour, (7) finding unusual patterns , (8) for evaluating learner's activities in order to adapt personalized resource deliver, (9) finding an ideal learning path, (10) generating personalized learning activities and assessment activities, (11) evaluating the progress of thread discussions and (12) providing feedback.
Student model can seen as a source of information about each student and it become prime module to drive the other modules of an ITS. The prominence of the proposed framework model in the virtual education is useful, (a) to build a student model into ITS, (b) to identify the cognitive and behavioral problems of adult learners, (c) provides guidelines to the teachers in order to design the course, (d) useful to the parents in order to understand the maturity level of cognitive and behavioral development of their own ward, (e) supports the virtual education system for virtual assistance, (f) useful for academic therapies like person-centered therapy, and cognitive behavioral therapy.

7. Conclusion

This research study is aimed to develop a student model for ITS using psychology datasets that are primary in nature. The initial phase of this research study started with Model-1 and Model-2 data modeling techniques. Using the two data models Personalized Profiling system (PPS) was developed to measure abilities, skills, interests, strengths, weakness and aspects of personality. Subsequently, statistical analyses were carried out in order to understand the inter relationships among thinking style, learning style, multiple intelligences and personality traits. The obtained Chi-Square results are shown the dependency association between 'Brain Dominances' and 'Multiple Intelligences' in the Model-2 dataset. Psychometric data clustering is one of the most challenging tasks for the researcher because of its uncertainty and diversified nature. To retain the property of 'interpretability' new clustering algorithm was proposed and name as men-difference clustering method. Since the primary data are highly diversified in nature; in order to categorize the students into four groups clustering was done.
Clustering is done to bring all the diversified students into four groups based on their competency level such as, excellent, good, average and poor competencies. Smaller number of categorization would be easier in providing the optimum solution for the activities like teaching, learning, mentoring, cognitive behavioral therapy, career optimization, etc.
In order to classify the unseen data both categorical data and numerical data sets are used. The clustered data is classified using 6 different classifiers and 5 different classifiers are used in order to induce an efficient classification. Finally, the framework model is proposed for an Intelligent Tutoring System (ITS) in order to provide a personalized education considering individual's thinking style, learning style, multiple intelligences and personality traits. The proposed 'Student Model' consists of Personalized Profiling System (PPS), classifier and the outcome of Analytical Hierarchical Process (AHP).
These inferences of this study can be used to develop courses and plan the teaching – learning processes effectively. This model evidently helps the teachers in order to address the issue of 'the Assistance Dilemma'. Moreover, this model identifies the needy people for 'Cognitive Apprenticeship" and 'Brain Literacy'. Student model can seen as a source of information about each student and it become prime module to drive the other modules of an ITS. The prominence of the proposed framework model in the virtual education is useful, (a) to build a student model into ITS, (b) to identify the cognitive and behavioral problems of adult learners, (c) provides guidelines to the teachers in order to design the course, (d) useful to the parents in order to understand the maturity level of cognitive and behavioral development of their own ward, (e) supports the virtual education system for virtual assistance, (f) useful for academic therapies like person-centered therapy, and cognitive behavioral therapy.

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