An Interactive Dynamic eLearning Framework for Visual and Verbal Learners

Mahendra A Sethi[#1], Santosh S Lomte[*2]
[#]Research Scholar, Department of CS&IT & Dr. B.A.M. University, Aurangabad (M.S.) India
[*]VDF's School of Engineering & Technology, Latur (M.S.) India.

Abstract

In this paper, an eLearning Framework to identify visual and verbal learners is proposed. The proposed framework identifies learning style using ILS Questionnaire based on Felder Silverman Learning Style Model. The learning strategies and learning assessment strategies of visual and verbal learners are identified using the two tests developed based on VARK model. The learner profile data is analyzed using K-Means algorithm to create learning style, learning strategy and assessment strategy clusters. The style specific learning objects are developed and delivered to learners using rule based method and FP Growth algorithm. This framework is useful for teachers to understand the learner and provide them personalized learning environment for improving the learning efficiency.

Keywords

eLearning, Learning Style, Visual/Verbal Learners, Learning Strategies, K-Means, Association Rule Mining, Dynamic eLearning

I. INTRODUCTION

In an online eLearning environment, learning contents are provided in a variety of formats including written text, images, graphs, charts, tables, audio, videos, animations etc. Most of the time the contents are mixed to suit the learners need. There are number of online learning sites available that provides learning contents to variety of purposes including educational content and skill improvement learning contents. Various intelligent tutoring systems are available that addresses the need of personalization. To learn the material or acquire the information learner uses various senses such as sight, hearing etc. Thus, visual and verbal is one of the learning dimension that considers how a learner receives learning information and what kind of learning content can benefit to the particular learning style. The learning contents / objects are the major source of input information for a learner who is learning in an online environment hence identification of visual and verbal learners in advance can help to build better learning experience and can enhance the learning efficiency by personalizing it.

Similarly, a learner can learn best by reading or listening. When the learning object is only text oriented or purely text / written instructions / words then the learner has to read it for understanding. If the learning object is in the form of audio-visual the learner has a scope for listening as well as reading. If the learner is learning through an audio tape then the learner has to listen it for acquiring the information. Most of the online learning environment use mixed objects which provides scope for reading and listening. Knowing the reading or listening preference in advance can help instructors to create the personalized learning objects for the learners.

In an eLearning environment, assessment of learner knowledge plays an important role in identifying whether the learner has understood and learned the topic of interest. Every individual has his own preferred way for answering the questions. Some are good in writing the explanations, some are good in answering the questions orally and some may be good in practical performance. Assessment through speaking and writing preferences can not only help learners to increase their confidence but also provide insights of what the learner has learned to the instructor. Hence identification of speaking and writing preferences will help instructors to design the personalized assessment strategy suitable to learners preferred style of answering the questions.

The proposed system identifies visual, verbal, listening, reading, speaking and writing preferences of a learner based on Felder Silverman and VARK Learning Style Model creates the clusters of learners using K-Means algorithm and delivers the style specific learning objects using rule base and FP Growth association rule mining algorithm. An instructional design process is developed in the form of storyboard template to help instructors for developing interactive learning objects.

II. RELATED WORK

In literature, there are numerous studies and experiments available that addresses the issue of learning style and need of personalization. Apart from Felder and Silverman [1], [2], [3], [4]. and VARK model other learning style models available are Dun and Dun Model, MBTI Model, David Kolb's Learning Style model etc. [34],[36]. Most of the studies are based on Felder and Silverman Learning Style Model which identifies the preferences over 8 learning styles grouped in 4 dimensions using ILS Questionnaire. VARK Questionnaire is used in VARK model to identify the preferences in four learning styles [5], [6], [7], [8], [9], [10], [11], [12], [13].

In a study conducted by PK Tulsi and etl… 175 students learning style was analysed using ILS, the results show there are differences among the learning styles of engineering students [14]. Lilita NN and etl… developed a framework for recommendation learning using ILS and data mining, the Decision Treee J48 algorithm were used for accuracy analysis which is achieved 76.92% [15]. A mobile based learning system implemented using fuzzy classifiers and FSLSM with 55 questions is used to analyse the differences among learning styles of Asian and African 83 students in [16]. Most of the studies available use ILS and FSLSM for data collection [17], [18], [24] from the learners and perform correlation analysis using ANOVA, Person Correlation Coefficient, Pared sample T test etc. [20], [21].

The studies based on VARK are model are also found suitable to predict the learning styles. [25], [26], [28], [29], [30]. These studies focus on determining learning preferences for visual, aural, read/write and kinaesthetic learning styles. Various data mining techniques including clustering, classification and pattern mining are used to analyse the data collected through learner behaviours and questionnaires [35], [37], [41]. The most widely used data mining techniques includes k-means clustering [34], [41], [43], fuzzy c-means [16], [41], Naïve Bays, J48 Decision Tree [15],[44], Rule based mining [37], FP Growth algorithm [43]. The impact of video based tutorials and platform for learning and development of video tutorial is discussed in [23]. ACO based adaptive eLearning system is discussed in [45].

III.PROPOSED SYSTEM

The figure 1 shows system architecture of "An Interactive Dynamic eLearning Framework for Visual and Verbal Learners" (IDEL). The system is developed using HTML, CSS, Java Script and Ruby programming language in Ruby on Rails (ROR) web application development framework. PostgreSql database is used to store all the data generated by users. The database contains two separate repositories, one for storing the user profile and activity data and other for storing the learning objects. Data mining techniques are used to analyse the data stored in these repositories.

As shown in figure 1 the learner has to sign up first using a web based interface to use the system. Once the learner provides required information he / she is directed to a web page that presents three tests sequentially. Learner is asked to solve three compulsory tests. The first test is for identification of learning style called V-Square Test. The second test is for identification of learning strategy called LST Test and third test is for identification of learning assessment strategy called LAST test. Upon completion of these test a learner profile is created and stored into database. Each learners record contains three important characteristics based on which three learner clusters are created using K-Means algorithm. Learning objects are delivered dynamically using rule based approach and FP Growth algorithm.

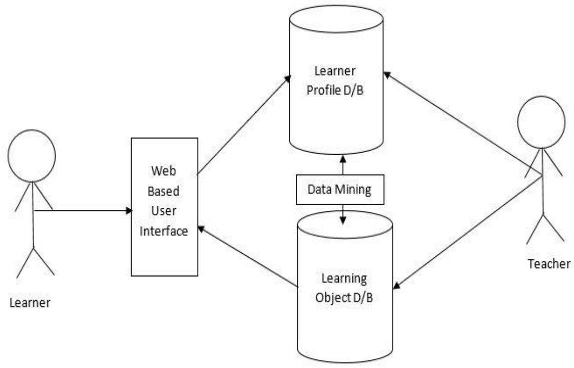

Fig 1: System Architecture of IDEL

IV.LEARNER MODEL

The static learner module is built using the data obtained from the three tests presented to learner in a web based eLearning environment. The scatter plot of the three attributes which are considered for building static model is as shown in figure 14. Based on the attribute values the learners have various preferences for the three dimensions visual / verbal, listening / reading and speaking / writing.

A. Identification of Visual and Verbal Preferences

As we are interested in identifying the visual and verbal learners hence only visual and verbal dimension of Felder Silverman Learning Style Model is considered in this experiment. 11 Questions [Q3, Q7, Q11, Q15, Q19, Q23, Q27, Q31, Q35, Q39, Q43] and two possible answers either "a" or "b" to each question taken from ILS Questionnaire is termed as V Square Test (VST) these questions identifies preference over visual and verbal dimension.

$$QVST=\{\mathbf{q1}_{V/V},\ldots,\mathbf{q11}_{V/V}\} \quad \ldots\ldots (1)$$

$$VST\_ans=\{\mathbf{a,b}\} \quad \ldots\ldots (2)$$

In each question, the answer "**a**" refers the visual pole and answer "**b**" refers to verbal pole. To find the visual or verbal preferences of learner we use a binary interval **[1,0]** to record the answers selected by learner for the questions in (1). "**1**" is recorded for each selected option and "**0**" is recorded for each unselected option.

In ILS, the preference for each pairwise coupled learning style dimension is expressed as an odd integer ranging [-11, +11], with steps of +/-2. Figure 2 shows the VST Scale used to map the preference value of a learner on visual and verbal dimension. To obtain the preference over visual and verbal pole of the learning dimension on VST Scale as shown in figure 2, a summation function of answers to questions belonging to a set of Questionnaire in (1) is used.

$$f(a,b) = \sum_{Qi=1}^{n=11} ai - \sum_{Qi=1}^{n=11} bi \quad \ldots\ldots (3)$$

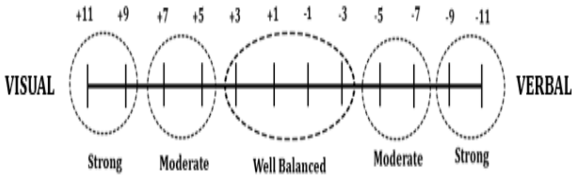

Fig 2: VST intensity scale

The result of equation (3) will give the preferences of visual dimension as a positive integers and preference over verbal dimension as negative integer values. For N number of learners, the equation (3) will produce a set of "**n**" preferences which is a universal set of learner preferences.

N = {X: $X_{vis/ver}$} ………… (4)

Where each "X_{vis}" is a visual preference value ranging from +1 to +11 with an increment step of +2 and each "X_{ver}" is a verbal preference value ranging from -1 to -11 with an increment step of -2.

1) Visual and Verbal feature vectors:

From VST intensity scale we can construct the set of visual and verbal features. The set of visual feature vectors (PVIS) is given by

PVIS= {+1,+3,+5,+7,+9,+11} ……….. (5)

The set of verbal feature vectors (PVER) is given by

PVER= {-1,-3,-5,-7,-9,-11} ………… (6)

B. Identification of Listening and Reading Preferences:

We are interested in identifying listening and reading preferences of the learners. Hence, we consider only two modalities Aural and Read/Write dimensions of VARK Model[25]. To identify listening or reading preference, Learning Strategy Test (LST) is constructed using 10 Questions (Q4, Q6, Q7, Q8, Q9, Q10, Q11, Q12, Q13, and Q15) and two possible answers either "a" or "b" to each question. The answer "a" indicates the listening preference and "b" indicates the reading preferences.

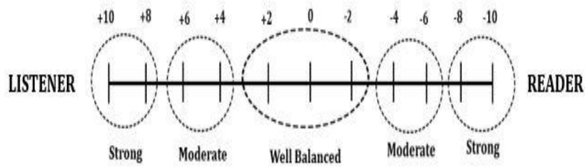

Fig. 3: LST intensity scale

A learning strategy intensity scale is constructed as shown in figure 3 using which one can identify the learning strategy intensity on a preferred pole of learning strategy dimension. The preference for each pole is expressed as an even integer ranging [-10, +10], with steps of +/-2 as shown in figure 3.

A set of questions called Learning Strategy Test (LST) is given in (7) and set of answers is given in (8).

QLST={**q1**$_{L/R}$,………,**q10**$_{L/R}$} ……… (7)

LST_ans= {**a, b**} ……….. (8)

To find the listening or reading preferences of learner we use a binary interval [1,0] and record the answers selected by learner for the questions in (7). "1" is recorded for each selected option and "0" is recorded for each unselected option.

To obtain the preference over listening and reading pole of the learning strategy dimension equation (3) is used. Preference on listening dimension is obtained as a positive integer value and preference over reading dimension is obtained as negative integer value. For N number of learners, the equation (3) will produce a set of "n" preferences which is a universal set of learner strategy preferences for listening and reading.

N={X:$X_{L/R}$} ………… (9)

Where, each $\mathbf{X_L}$ is a listening preference value ranging from +2 to +10 with an increment step of +2, each $\mathbf{X_R}$ is a reading preference value ranging from -2 to -10 with an increment step of -2, and 0 is neutral or well-balanced preference on either dimension.

1) Listening and Reading feature vectors:

From LST intensity scale we can construct the set of listening and reading features. The set of listening feature vectors (LF) is given by

LF = {+2, +4, +6, +8, +10} …………… (10)

The set of reading feature vectors (RF) is given by

RF = {-2, -4, -6, -8, -10} ………… (11)

C. Identification of Speaking and Writing Preferences:

We are interested in identifying speaking and writing preferences of the learners. Hence, we consider only two modalities Aural and Read/Write. To identify speaking or writing preference Learning Assessment Strategy Test (LAST) is constructed using 06 Questions (Q1, Q2, Q3, Q5, Q14, and Q16) and two possible answers either "a" or "b" to each question. The answer "a" indicates the speaking preference and "b" indicates the writing preferences.

A learning assessment strategy intensity scale can be constructed as shown in figure 4 using which one can identify the learning assessment strategy intensity on a preferred pole of learning assessment strategy dimension. The preference for each pole is expressed as an even integer ranging [-6, +6], with steps of +/-2 as shown in figure 4.

A set of questions called Learning Assessment Strategy Test is given by (12) and set of answers is given by (13).

QLAST={**q1**$_{S/W}$,………….,**q6**$_{S/W}$} ……. (12)

LST_ans={**a, b**} ….……… (13)

To find the speaking or writing preferences of learner we use a binary interval [1,0] and record the answers selected by learner for the questions in equation (12). "1" is recorded for each selected option and "0" is recorded for each unselected option. To obtain the preference over speaking and writing pole of the learning assessment strategy dimension equation (3) is used.

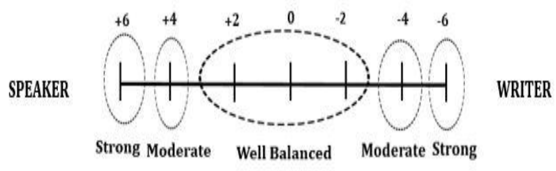

Fig 4: LAST intensity scale

The result of equation (3) will give the preferences of speaking dimension as a positive integer and preference over writing dimension as negative integer value. For N number of learners, the equation (3) will produce a set of "n" preferences which is a universal set of learner preferences.

$$N=\{X:_{S/W}\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where, each X_S is a speaking preference value ranging from +2 to +6 with an increment step of +2, each X_W is a reading preference value ranging from -2 to -6 with an increment step of -2, and 0 is neutral or well-balanced preference on either dimension.

1) Speaking and Writing feature vectors:

From LAST intensity scale, we can construct the set of speaking and writing features. The set of speaking feature vectors (SF) is given by

SF= {+2, +4,+6} ……………… (15)

The set of writing feature vectors (WF) is given by

WF= {-2,-4,-6} ………………. (16)

V. LEARNER PROFILE DATA

Once the learner completes the test and data is stored in the database. The learner can be assigned three attributes depending upon the preference count and the feature vector of each pole in three dimensions.

A. Learning Style Attribute:

From the learning style feature vectors given in (5) and (6), and the VST Scale intensity shown in figure 2 we can form the new learning styles on visual and verbal dimensions as shown in table 1. The learner will possess one of the new learning style.

Table 1: Learning Style Attribute Values

LS Attribute	FV Value
Visual	+11, +9
Verbal	-11, -9
Visually &Verbally Balanced	+3, +1, -1, -3
Visually Inclined	+7, +5
Verbally Inclined	-7, -5

B. Learning Strategy Attribute:

From the learning strategy feature vectors given in (10) and (11), and the LST Scale intensity as shown in figure 2 we can form the learning strategy attribute on listening and reading poles of learning strategy dimension as shown in table 2. The learner will possess one of the new learning strategy.

TABLE 2: LEARNING STRATEGY ATTRIBUTE VALUES

LST Attribute	FV Value
Active Listener	+10, +8
Inclined Listener	+6, +4
Balanced Listener and Reader	+2, 0, -2
Inclined Reader	-6, -4
Active Reader	-10, -8

C. Learning Assessment Strategy Attribute:

From the learning assessment strategy feature vector given in (15) and (16), and the LAST Scale intensity as shown in figure 4 we can form the learning assessment strategy attribute on speaking and writing poles of learning assessment strategy dimension as shown in table 3. The learner will possess one of the new learning strategy.

TABLE 3: LEARNING ASSESSMENT STRATEGY ATTRIBUTE VALUES

LAST Attribute	FV Value
Active Speaker	+6
Inclined Speaker	+4
Balanced Speaker and Writer	+2, 0, -2
Inclined Writer	-4
Active Reader	-6

VI. FORMATION OF LEARNER CLUSTERS

The three attribute values are used to form the different learner clusters using K-Means algorithm. Initially three learning style clusters visual, verbal and balanced are formed using learning style attribute. Then each learning style cluster is divided in three learning strategy clusters as active listener, active reader and balanced listener reader. The learning style clusters are again divided into three learning assessment strategy clusters as active speaker, active writer and balanced speaker-writer. As shown in figure 14 the blue points are the learning preference of a learner in visual and verbal dimension, red points indicate the listening and reading preferences and green points represent the speaking and writing preferences of a learner.

A. K-Means Clustering Algorithm:

Clustering allows to classify and group the instances into a similar group called cluster. Hierarchical clustering and Partitional clustering are the two categories of clustering algorithms. In partitional clustering clusters are created using the optimized criteria function for partitioning the objects into clusters. The k-means algorithm uses a squared error criterion and iteratively generate cluster centre.

Given K, the number of clusters, the numeric K-Means clustering algorithm randomly assigns each data point to a cluster. For each cluster, the cluster center is a vector of length m. Each entry in the vector is defined as the average value of the corresponding attribute, across all data points in the cluster. Data points are then assigned to the closest cluster centre.

Let xn be the nth data point, and let cck be the centre of the kth cluster. The squared Euclidian distance d(xn,k) between xn and cck is given by Equation 17, where xnm is the mth component of xn and cckm is the mth component of cck .

$$d(x_n, k) = \sum_{m=1}^{M} (x_{nm} - cc_{km})^2 \quad ....(17)$$

The data point is then assigned to the cluster that minimizes the Euclidean distance, d(xn,k).

d (xn, k) min = min {d (xn,1), d (xn,2), ..., d (xn, K)} ……... (18)

Using the revised cluster assignments, each new cluster center is defined as the average value of each attribute, across all data points in the new cluster. Cluster center and assignment is iterated till all data points are assigned a unique cluster.

B. *Learning Strategy Clusters:*

As shown in figure 5, the learner will adopt any one of the learning strategy. Using these learning strategies, the instructor can design the personalized learning objects which match the preferred learning strategy of a learner. The K-Means algorithm is used to create the nine learning strategy clusters.

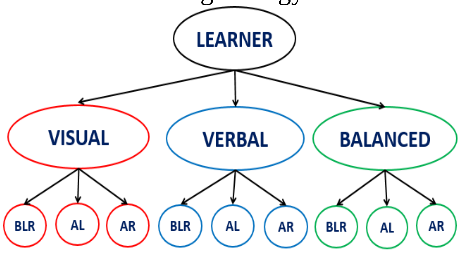

Fig 5: Learning Strategy Clusters

C. *Learning Assessment Strategy Clusters:*

As shown in figure 6, the learner will prefer one of the learning assessment strategy. Using this assessment strategies, the instructor can design the assessment that can better assess the learner. The K-Means algorithm is used to create the nine learning strategy clusters.

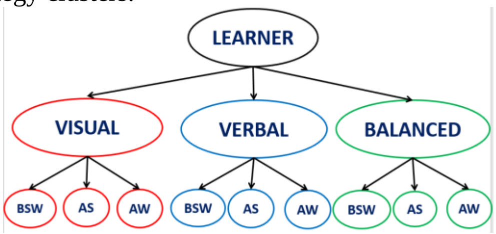

Fig 5: Learning Assessment Strategy Clusters

VII. LEARNING OBJECT DEVELOPMENT

The aim is to develop interactive and style specific multi-version learning objects for that studying various instructional design theories, models and process we have developed a storyboard template. As discussed in literature survey Felder Silverman and VARK learning style model suggests learning contents and teaching strategies based on which we have identified the content type that is suitable to a particular learning style and strategies. Each learning object will have learning contents that possess characteristics as listed below.

CS_1: {Written Text and Diagrams / Graphs / Flowcharts / Tables / Pictures / Images}

CS_2: {Written Text, Audio Narration, and Images / Flowcharts / Diagrams / Tables}

CS_3: {Recorded Video Lectures with Audio and text}

CS_4: {Written Text with Important word highlighted / underlined, different font styles}

CS_5: {Written Text & Audio Narration}

CS_6: {Podcast / Audio Tape}

TABLE 4: LEARNING OBJECT TABLE

Learning Style	Learning Object	Characteristics	LST Feature
Visual	VIS_LO_1	CS_1	Reading
	VIS_LO_2	CS_2	Reading & Listening
	VIS_LO_3	CS_3	Listening &Reading
Verbal	VRB_LO_1	CS_4	Reading
	VRB_LO_2	CS_5	Reading & Listening
	VRB_LO_3	CS_6	Listening

VIII. DELIVERING LEARNING OBJECTS

Initially the learning objects are delivered using the rule based approach according to learning style attribute of three learning style clusters obtained in static model. For individual learner of each cluster a learning object recommender system is developed based on FP Growth algorithm.

A. *Delivering Learning Objects in Static Model*

A rule based approach is used to deliver the learning objects based on the learning style attribute. The rule base is as explained below. As shown in table the system delivers the learning objects to the learners in each cluster.

TABLE 5: RULE BASE TO DELIVER LEARNING OBJECTS

Rule	Rule
RULE 1	IF LS = VIS AND LST=AL THEN Show LO_TYPE = VIS_LO_3, VIS_LO_2, VIS_LO_1
RULE 2	IF LS = VIS AND LST= AR THEN Show LO_TYPE = VIS_LO_1, VIS_LO_2, VIS_LO_3
RULE 3	IF LS = VIS AND LST=BLR THEN Show LO_TYPE = VIS_LO_1, VIS_LO_2, VIS_LO_3
RULE 4	IF LS = VER AND LST = AL THEN Show LO_TYPE = VER_LO_3, VER_LO_2, VER_LO_3
RULE 5	IF LS = VER AND LST = AR THEN Show LO_TYPE = VER_LO_1, VER_LO_2, VER_LO_3

RULE 6	IF LS = VER AND LST = BLR THEN Show LO_TYPE = VER_LO_1, VER_LO_2, VER_LO_3
RULE 7	IF Learner C_TYPE = = VIS THEN Show LO_TYPE = = ALL

B. Learning Object Recommender System:

This step adds more personalization of learning objects based on learning object access patterns. In this system, we use FP Growth algorithm to recommend the learning objects to learners in visually and verbally balanced clusters.

1) FP Growth Algorithm:

It is one of the association rule mining algorithm. Association rule mining is used to analyse the correlation between items. Market basket analysis is popular application of association rules. Support, Confidence and Lift are the important properties of association rules. To predict or find the desired rule that satisfies the minimum confidence set of items is found having greater or equal support from the given item set. Consider for example I= {I1, I2, …, In} is a set of items, 'D' is a transaction database having a unique identifier TID for every transaction, and every transaction $T \subseteq J$. The transaction T contains A if $A \subseteq T$ and A is a set of items. An association rule implies relationship among A and B, when $A \subset J$, $B \subset J$ and $A \cap B = \phi$. As discussed earlier the two important properties Support and Confidence are defined as follows:

Support: P(AUB), which is the probability that A or B appears in the transaction set D.

Support=Freq(A,B)/N ………... (19)

Confidence: P(B|A), which is the probability that A and B both appears at the same time in the transaction set D.

Confidence=Freq (A, B)/Freq(A) …………… (20)

The rules created using FP Growth algorithm are strong rule when each rule satisfies the minimum support and minimum confidence threshold. The algorithm uses divide and conquer strategy to create FP-Tree of frequent item sets by compressing the transaction database. This compressed database is divided into a set of conditional databases of frequent item set and data mining is performed on each conditional database.

FP-Tree: Sort data items in the transaction data table by support, then insert the data items in each transaction into a tree with NULL as its root by descending turn and record the support of each node occurs.

Conditional pattern base: Contains the set of prefix path which appears together with the suffix pattern set in the FP-Tree.

Condition tree: Construct the conditional pattern base into a new FP-Tree according to the principles of the formation of FP-Tree.

FP-Tree is constructed using 2 passes over the dataset:

Pass 1:

1. Scan database and find single item frequency.
2. Remove infrequent items i.e. items having frequency less than minimum threshold support.
3. Sort frequent items in frequency descending order and name it as a "L" list /table.

Use this order when building the FP-Tree, so common prefixes can be shared.

Pass 2: Construct the FP Tree.

Each item in FP tree is a node and has a counter.

1. Read one transaction at a time and map it to a path
2. Use fixed order so that paths can overlap when transactions include same items.
3. Maintain pointer links between nodes containing the same item.
4. Extract the set of frequent items from the FP-Tree.

Thus, the algorithm can be summarized as we recursively construct and mine the FP trees until the resulting FP tree is empty or it contains only one path. This single path generates all the combinations of its sub paths each of which is a frequent pattern.

The table 4.6 shows the first five transactions patterns in which a learner has accessed the learning objects. Using this transaction table, the FP Growth algorithm recommends the items as shown in table 4.9. We have assumed minimum support threshold value min_sup =2. For simplicity A represents VIS_LO_1, B represents VIS_LO_2, C represents VIS_LO_3, D represents VER_LO_1, E represents VER_LO_2 and F represents VER_LO_3.

TABLE 6: LEARNING TRANSACTIONS

Transaction ID	Learning Objects
T1	A, B
T2	B, D, C
T3	A, D, C, E
T4	A, D, E
T5	A, B, C

Create a table L by observing the frequency of each item and removing the items having frequency less than min_support=2. Sort the items in decreasing order of frequency as shown in table 7. Create a corresponding FP tree as shown in figure 6.

TABLE 7: FREQUENCIES OF LEARNING OBJECT

Learning Objects	Frequencies
A	4
B	3
D	3
C	3
E	2

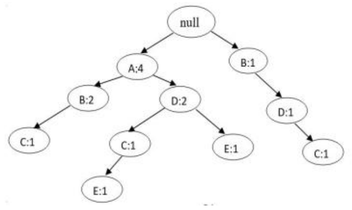

Fig 6: FP Tree of Transaction Table

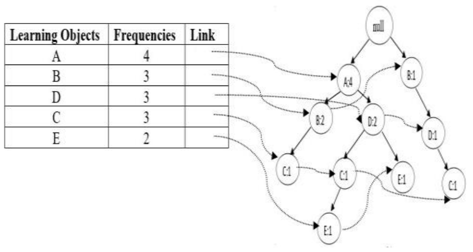

Fig 7: Construction of FP Tree with links to frequent objects

After generation of FP tree, we can mine the results. Start with leaf node

Table 8: Pattern And Tree Link Support

Learning Objects	Conditional Pattern Base	Conditional Tree	Frequent Learning Objects
E	{{A, D, C:1}, {A, D:1}}	{<A:2, D:2>}	**{A, E}:2, {D, E}:2, {A, D, E}:2**
C	{{A, B:1}, {A, D:1}, {B, D:1}}	{<A;2, <B:1>, <D:1>>, <B:1, D:1>}	**{A, C}:2, {B, C}:2, {D, C}:2**
D	{{A:1}, {B:1}}	{<A:2>}	**{A, D}:2**
B	{A:2}	{<A:2>}	**{A, B}:2**

Frequent Pattern Set with minimum support count which can be recommended to a learner are as shown in table 4.9.

Table 9: Object Recommender Pattern

Frequent Pattern	Support Count
2-Item set	
{A, B}	2
{A, C}	2
{A, D}	2
{A, E}	2
{B, C}	2
{C, D}	2
{D, E}	2
3-Item set	
{A, D, E}	2

IX. RESULTS & DISCUSSION

A. Results of VST:

As shown in Fig 8 & 9 out of N=62, 16 learners are visual, 21 learners are visually inclined, 14 learners are visually and verbally balance, 4 learners are verbally inclined, and 7 learners are verbal. Using K-Means clustering the data obtained through VST is clustered into three clusters. The visual learner cluster contains 26% learners, the verbal learner cluster contains 11% learners and remaining 63% learners are the part of visually and verbally balanced learner cluster.

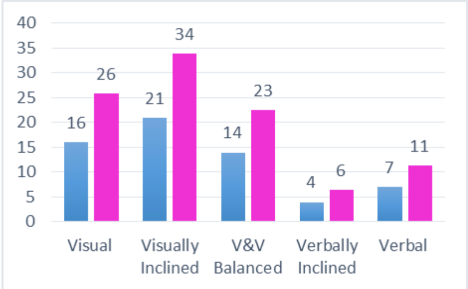

Fig 8: Result of VST

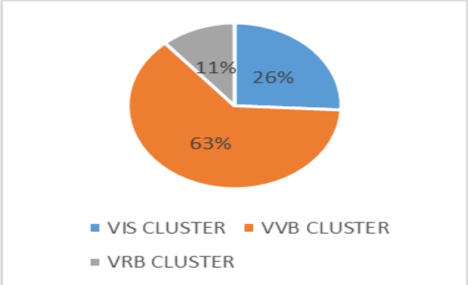

Fig 9: Learner Clusters

B. Results of LST:

As shown in Fig 10 & 11 out of N=62, 8 learners are active listeners, 22 learners are inclined towards listening, 21 learners are balanced listeners and readers, 6 learners are inclined towards reading, and 5 learners are active readers. Using K-Means clustering the data obtained through LST is clustered into nine clusters with respect to learning style clusters. The following pie chart show the division of learners with respect listening and reading strategies into three major clusters of interest. The active listener cluster contains 13% learners, the cluster of active reader contains 8% learners and cluster of balanced listener reader contains 79% learners who belong to one of the learning style clusters generated by LST.

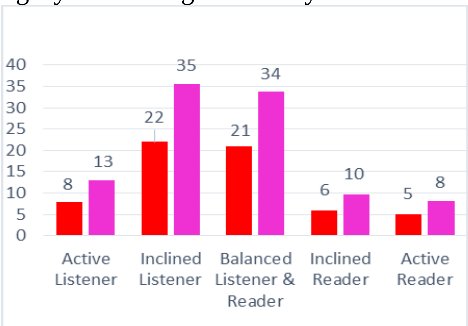

Fig 10: Result of LST

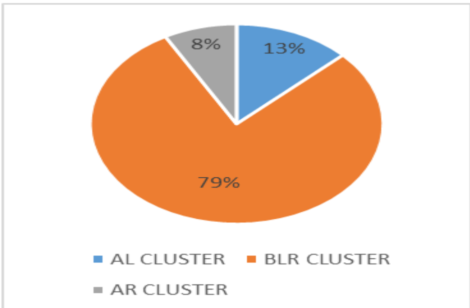

Fig 11: Learning Strategy Clusters

C. *Results of LAST:*

As shown in Fig 12 & 13 out of N=62, 6 learners are active speakers, 11 learners are inclined towards speaking, 31 learners are balanced speakers and writers, 9 learners are inclined towards writing, and 5 learners are active writers. Using K-Means clustering the data obtained through LAST is clustered into nine clusters with respect to learning style clusters. The graph 5.6 shows the division of learners with respect speaking and writing strategies into three major clusters of interest. The active speaker cluster contains 10% learners, the cluster of active writer contains 8% learners and cluster of balanced listener reader contains 82% learners who belong to one of the learning style clusters generated by LAST.

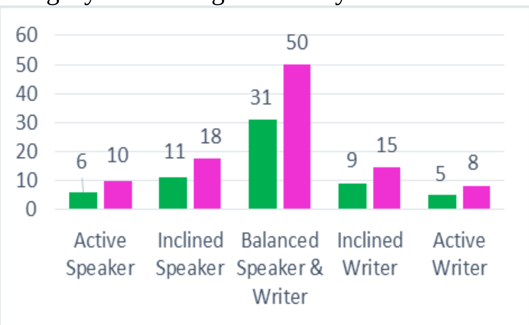

Fig 12: Result of LAST

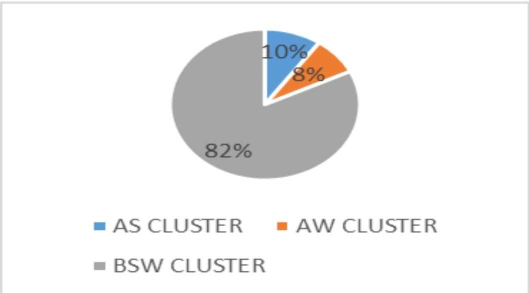

Fig 13: Learner Assessment Strategy Clusters

D. *Results of Learning Object Delivery:*

Learning objects are delivered using two methods. In first method learning objects are delivered using a rule based approach and then a learning object recommender system dynamically recommends the learning objects based on the frequent access patterns which are constructed using the first 10 transactions of each learner in visually and verbally balanced cluster.

1. *Learning Object Delivery in Visual Cluster:*

The table 10 summarizes the access frequency of learning objects in visual learner style cluster according to the learning strategy of individual learner.

TABLE 10: LO DELIVERY AND ACCESS COUNT

RULE	Learning Strategy	Learners	LO Access Count in %		
			VIS_LO_1	VIS_LO_2	VIS_LO_3
RULE 1	VISUAL ACTIVE LISTENR	07	28%	86%	100%
RULE 2	VISUAL ACTIVE READER	00	00 %	00 %	00 %
RULE 3	VISUAL BALANCED LISTENER READER	09	33%	78%	44%

2. *Learning Object Delivery in Verbal Cluster:*

The table 11 summarizes the access frequency of learning objects in verbal learner style cluster according to the learning strategy of individual learner.

Table 11: Object Delivery and Access Count

RULE	Learning Strategy	Learners	LO Access Count in %		
			VER_LO_1	VER_LO_2	VER_LO_3
RULE 4	VERBAL ACTIVE LISTENR	-	-	-	-
RULE 5	VERBAL ACTIVE READER	04	100%	75%	25%
RULE 6	VERBAL BALANCED LISTENER READER	03	100%	100%	100%

3. *Learning Object Delivery in Visually & Verbally Balanced Cluster:*

The table 12 summarizes the access frequency of learning objects in visually and verbally balanced learner style cluster according to the learning strategy of individual learner.

Table 12: Object Delivery and Access Count

RULE	Learning Strategy	Learners	LO Access Count in %		
			VIS_LO_1	VIS_LO_2	VIS_LO_3
RULE 7	BALANCED	39	23%	54%	41%
			LO Access Count in %		
			VIS_LO_1	VIS_LO_2	VIS_LO_3
			23%	54%	41%

E. *Learning Object Recommender System:*

To recommend the learning objects dynamically we have used FP Growth algorithm for the learners in visually and Verbally Balanced Cluster. Table 4.9 shows the frequent access patterns of learning object by a learner. Based on which the learner can be recommended learning object A when he access any one of the learning objects among B, C, D, E. Similarly, for all learners in we have created a pattern base to recommend the learning objects.

F. *Reliability of the system.*

Test-Retest Reliability is found using Pearson Correlation Coefficient "r" is calculated with following formula.

$$r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma y)^2]}}$$

Where, n = number of learners
Σx = sum of x scores in test 1
Σy = sum of y scores in test 2
Σxy = sum of the products of paired scores
Σ x2 = sum of squared x scores
Σy2= sum of squared y scores

Table 13: Pearson Correlation Coefficient Value (r)

Test	Value of r	Remark
V-Square Test (VST)	0.9966	Strong Positive Correlation
Learning Strategy Test (LST)	0.9904	Strong Positive Correlation
Learner Assessment Test (LAST)	0.6698.	Moderate Positive Correlation

X. CONCLUSION

This research work has proposed a multimodal collaborative approach for identification of visual and verbal learners, learning strategies, estimating learner assessment strategies using Felder Silverman Learning Style Model and VARK Model. Using K-Means clustering algorithm the data obtained through tests is clustered into learning style, strategy and assessment clusters. Learning objects are delivered to learners using rule based approach and learning object recommender system is built using FP Growth algorithm.

For N=62, the results of VST test found 16 learners having visual learning style, 21 learners are visually inclined, 14 learners are visually and verbally balanced, 4 learners are verbally inclined, and 7 learners are verbal. The visual learner cluster contains 26% learners, the verbal learner cluster contains 11% learners and remaining 63% learners are the part of visually and verbally balanced learner cluster.

The results of LST indicates, 8 learners as active listeners, 22 learners are inclined towards listening, 21 learners are balanced listeners and readers, 6 learners are inclined towards reading, and 5 learners are active readers. The active listener cluster contains 13% learners, the cluster of active reader contains 8% learners and cluster of balanced listener reader contains 79% learners.

Similarly results of LAST test found, 6 learners as active speakers, 11 learners are inclined towards speaking, 31 learners are balanced speakers and writers, 9 learners are inclined towards writing, and 5 learners are active writers. The active speaker cluster contains 10% learners, the cluster of active writer contains 8% learners and cluster of balanced listener reader contains 82% learners.

The rule based approach delivered style specific contents to visual and verbal learner clusters. The learners in visual clusters accessed learning objects according to their preferred way of learning. Learning object access percentage for three types of visual learning object by Visually Active Listener is observed as 28%, 86%, and100% respectively. Learning object access percentage by Visually Balanced Listener Reader is observed as 33%, 78%, and 44% respectively. Similarly, the learning object access percentage for three types of verbal learning objects by verbally active reader 100%, 75% and 25% and verbally balanced listener reader is observed as 100%. Finally, for the learners in visually and verbally balanced clusters the learning object recommender system recommends the style specific learning objects by mining learning object access patterns.

The reliability of V-Square Test (VST) with value of ***r=0.9966*** indicates the strong positive correlation among test items. Similarly, reliability of Learning Strategy Test (LST) with value of ***r=0.9904*** indicates strong positive correlation among test items. Reliability of Learner Assessment Test (LAST) with value of ***r=0.6698*** indicates moderate positive correlation.

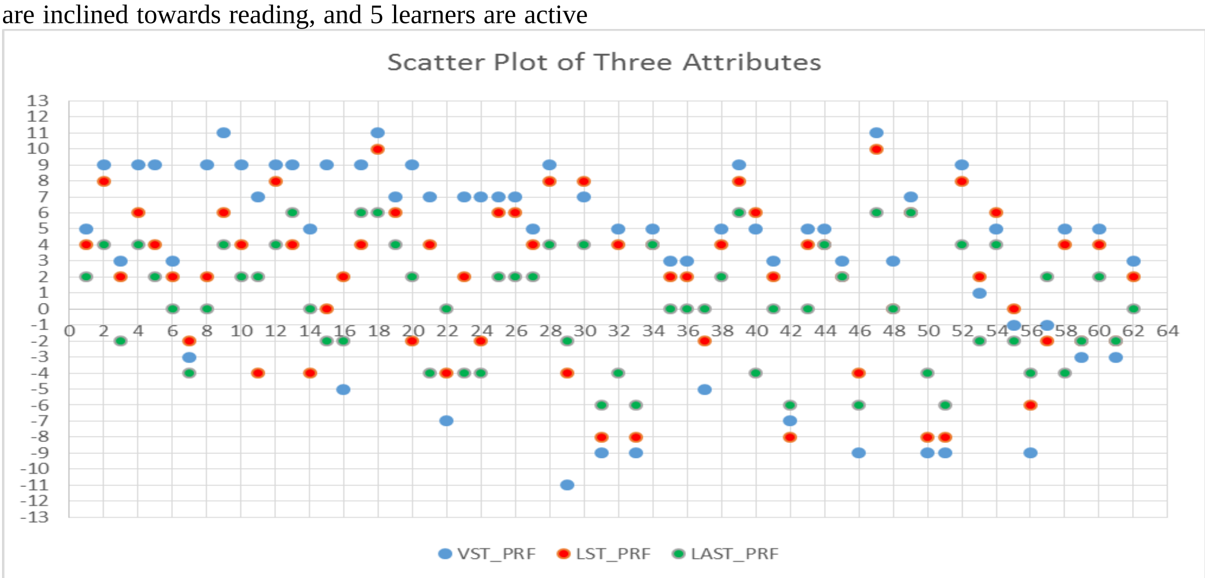

Fig 14: Scatter Plot of LS, LST and LAST attribute values of learners

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