# Impact of Learning Style and Personality Traits on Students' in Academics

**Amala Jayanthi. M, Lakshmana Kumar.R, Hari Priya.K.P**

***Abstract: The objective of education exclusively aims on students. The goal of education said to be achieved once the students' knowledge, skill set and attitude is groomed under the efficient supervision of well-trained educators. Benjamin Bloom's theory on learning process, a person not only get groomed in his knowledge and mental abilities (i.e. Cognitive) but also in his emotions (i.e. Affective).One's personality is defined as the unification of emotional, attitudinal, behavioral responses (i.e. Affective). Learning is the way toward getting new data or capacity to fabricate data from definitely known data.Learning is influenced by the human behavior (i.e. Affective).Human behavior is influenced by the living environment. Education aims to provide efficient and peaceful environment to mold students' personality and learning skills. Educational Data Mining is one of the budding applications in educational sector. It helps to understand better the students' learning activity and their overall involvement in the activity. This allows the further improvement of the quality and the productivity of the educational system. Eysenck Personality Inventory and Criterion Reference Model used to determine the personality of the students. This exploration is to contemplate the impact of the Personality characteristics and Learning Styles on the scholarly execution of the understudies as indicated by Bloom's Theory. Eysenck Personality Inventory and Criterion Reference Model used to decide the identity of the understudies. Supervised and unsupervised techniques are used to analyze students' dataset. Students are clustered based on the Personality, Learning Style and Performance by employing Multi-Layer Perceptron and EM clustering Technique. Descriptive and Predictive modelling is applied to determine the association between students' Personality, Learning Styles and Academic Performance using mapping or function. The study depicts the existence of positive correlation between student's Personality traits, Learning styles and Academic Performance. This research helps the educators to understand students' Behavioral, Attitudinal and Emotional Growth during the learning process as a Personality and their learning ability. It helps the educators' to provide appropriate training for improving their expertise in academics accordingly.***

***Keywords: Multi-Layer Perceptron (MLP), Expectation Maximization (EM) clustering, Criterion Reference Model, Bloom's Taxonomy, Honey and Mumford's Learning Questionnaire, Eysenck Personality Questionnaire, Personality Types.***

## I. INTRODUCTION

Educational Data Mining is blooming research area. Educational Data Mining explore the unique data values in educational environment using various data mining methods that allows the better understanding of students' in the academic environment. Honey and Mufford Learning Style Questionnaire and Eysenck Personality Questionnaire have been used to determine students' Learning Style and Personality respectively. Criterion Reference Model is employed to cluster students' academic performance. The marks obtained in the theory and programming can be viewed as their performance. This study deals with educational objectives that determine students' academic performance with respect to their Learning style and Personality. Students' are categorized based on their respective Personality and Learning Style using EM clustering technique [25]. Likewise students' performance is classified as High, Average, and Low. Students' sub categories are identified using MLP. It allows to identify the pattern of subcategories by classifying with results in useful information through mining similarly, the academic performance of the students' also classified. Supervised and Unsupervised Learning Process is implied to find the correlation Learning style, Personality type and Academic Performance based on Supervised and Unsupervised Learning Process[27]. Apriori rule mining algorithm has been employed to derive rules based on the association between the Learning Style, Personality and Academic Performance.

## II. MOTIVATION

### A. Bloom's Taxonomy

Benjamin Bloom, educationalist formulated the learning theory with three domains Cognitive Domain (Intellectual), Affective Domain (Emotional), and Psychomotor (Skills). Affective domain deals with emotional process such as feelings, values, appreciation, interest, motivation and attitude. Receiving, Responding, Organizing, Valuing, and Internalizing are the levels of affective domain. According to Bloom, mastering previous level should be prior in moving to the next. Learning is the ability to build information by practice and experience. Learning style is influenced by attitude or behaviour (Affective).Learning style is determined by Honey and Mumford Learning Style Questionnaire. Personality is defined to be the Intrinsic factor of Affectivity. Students' Personality Type is evaluated by Eysenck Personality Questionnaire.

### B. Honey and Mumford Learning Style Questionnaire

The Honey and Mumford Learning Style Questionnaire comprises of 80 items of Yes/No Pattern [1]. It is internationally proven device developed by Peter Honey and Alan Mumford. The questionnaire is devised to find the learning style preferred by the participant.

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Each response of the respondent describes his/her feelings over the past week. According to the score calculated with respect to the responses of 80 items, the participants are grouped as Activist, Reflector, Theorist, Pragmatist .

### C. Eysenck Personality Inventory

Eysenck Personality Questionnaire (EPQ)[1,2] assess a person's personality. Hans Jürgen Eysenck and his wife Sybil B. G. Eysenck, psychologists, devised the questionnaire. The Inventory constitutes 100 items of Yes/No Questions. Each respondent has to answer in each group that describes the his/her feelings over the past week. The score is calculated based on the responses of the items and with the score the respondent is categorized under their personality as Extroversion, Neuroticism, and Introvert.

### D. Criterion Reference Model:

The Goal attainment of the course by the student is assessed by Criterion Reference Model. Based on a particular criterion assessment is carried out. The students' academic performance is mapped with the given criterion and expressed as results. The result is stated based on the standard that students have achieved on the criteria [21].

### E. Expectation Maximization (EM) clustering:

The EM algorithm is an iterative refinement clustering algorithm. It is used to find the parameter estimation. According to the cluster mean calculated similar objects are put into same cluster. Based on the weight that represents the membership probability, each object is assigned to the dedicated cluster. There is no restriction between the cluster boundaries. And so based on weighted measures, new means are calculated.[22]

### F. Multi-Layer Perceptron:

Multi-Layer Perceptron is one of the classification techniques. It is a network of simple neurons called Perceptron. The Perceptron computes a single output from multiple real valued inputs by forming a linear combination according to its input weights and then possibly putting the output through some nonlinear activation function.

## III. HMLEPP APPROACH

In phase 1, Honey and Mumford Inventory for learning style is pretested. After pretesting the questionnaire, post-graduation students were subjected to analyze test. The preferred learning style of the student participants is determined. As Learning Style the Personality type of the students is evaluated by Analyze test conducted with Eysenck Personality Inventory after pretesting to the same set of participants. Based on the result of analyze test the student participants are grouped under their own Personality and Learning Style respectively[28,29,30]. The marks secured in written is considered as input to assess the performance of the student participants. They are categorized under High (marks ≥ 70), Average (marks ≥ 50) and Low (marks<50) based on Criterion Reference Model. The student Data set that contains the result of the Analyze tests of Eysenck Personality Inventory, Honey and Mumford Learning Style and Academic Performance of the students.

In phase 2, 3 and 4, the association between the Personality Trait, Learning Style and Academic Performance is discovered using Data Mining methods, EM clustering and Multi-Layer Perceptron. The students are designated under the clusters based on their preferred learning style as Activist, Reflector, Theorist and Pragmatist. Similarly the students are clustered respectively Extroversion, Neuroticism, Introvert according to their Personality and as High, Low and Average based on their performance. Students are categorized under personality, learning style and academic performance based on MLP classification technique.

In phase 4, the association between the Personality, Learning Style and the Performance of the student participants are discovered using Apriori algorithm

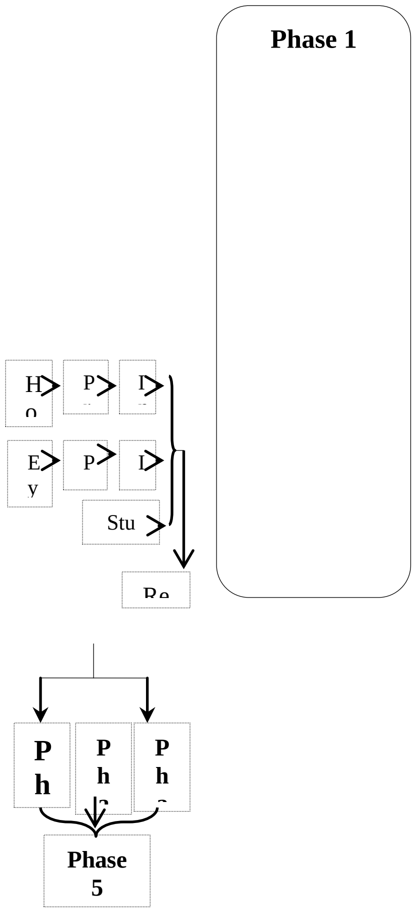


Figure 1 HMLEPP APPROACH

## IV. RESULTS AND DISCUSSIONS

From the dataset containing 444 dataset, association between Personality, Learning Style and academic performance is analysed.


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TABLE I. CLUSTER ASSIGNMENTS AND LEARNING STYLES

| C0 | C1 | C2 | C3 | Learning Style |
|---|---|---|---|---|
| 96 | 0 | 0 | 0 | Activist |
| 0 | 108 | 0 | 0 | Pragmatist |
| 0 | 0 | 168 | 0 | Theorist |
| 0 | 0 | 0 | 72 | Reflector |

Table I depicts the various clusters and corresponding Learning Style. It reveals that the students are grouped in cluster 0(Activist), cluster 1(Pragmatist), cluster 2(Theorist) and cluster 3(Reflector) respectively based on their Learning Style.

TABLE II. CONFUSION MATRIX FOR LEARNING STYLE

| **Cross Validation** | | **Predicted** | | | | |
|---|---|---|---|---|---|---|
| | | ***a*** | ***b*** | ***c*** | ***d*** | ***Learning Style*** |
| Actual | A | 96 | 0 | 0 | 0 | Activist |
| | B | 0 | 10 8 | 0 | 0 | Pragmatist |
| | C | 0 | 0 | 16 8 | 0 | Theorist |
| | D | 0 | 0 | 0 | 72 | Reflector |

Table II shows the confusion matrix for the learning styles. The confusion matrix reveals that various classes using 4 sigmoid nodes.

TABLE III. : CLUSTER ASSIGNMENTS AND PERSONALITY TRAITS

| **C0** | **C1** | **C2** | **Personality** |
|---|---|---|---|
| 96 | 0 | 0 | Extrovert |
| 0 | 168 | 0 | Neuroticism |
| 0 | 0 | 180 | Introverts |

Table III depicts the various clusters and corresponding Personality types as Extroversion, Neuroticism and Introvert are grouped in cluster 0, cluster 1 and cluster 2 respectively.

TABLE IV. CONFUSION MATRIX FOR PERSONALITY

| **Cross Validation** | | **Predicted** | | | |
|---|---|---|---|---|---|
| | | **a** | **b** | **c** | **Personality** |
| Actual | A | 96 | 0 | 0 | Extrovert |
| | B | 0 | 168 | 0 | Neuroticism |
| | C | 0 | 0 | 180 | Introverts |

Table IV shows the Confusion Matrix for Personality. The Confusion Matrix reveals that various classes using 3 sigmoid nodes to identify 3 different personality categories.

TABLE V. CONFUSION MATRIX FOR PERFORMANCE

| Cross Validation | | Predicted | | | |
|---|---|---|---|---|---|
| | | a | b | c | Performance |
| Actual | A | 204 | 0 | 0 | High |
| | B | 0 | 72 | 0 | Average |
| | C | 0 | 0 | 168 | Low |

Table V depicts the Confusion Matrix for Performance. The Confusion Matrix of 3 sigmoid nodes that reveals the existence three various classes .

TABLE VI. CLUSTER ASSIGNMENTS AND PERFORMANCE

| C0 | C1 | C2 | Performance |
|---|---|---|---|
| 204 | 0 | 0 | High |
| 0 | 72 | 0 | Average |
| 0 | 0 | 168 | Low |

Table 6 reveals the students are grouped under various clusters of performance scale. (High, Average and Low)

TABLE VII. ASSOCIATION RULES MINED

1. personality category=Neuroticism 168 ==> Learning category=Theorist 168 <conf:(1)>
2. Learning category=Theorist 168 ==> personality category=Neuroticism 168 <conf:(1)>
3. Performance=Low 168 ==> Learning category=Theorist 168 <conf:(1)>
4. Learning category=Theorist 168 ==> Performance=Low 168 <conf:(1)> 5. Performance=Low 168 ==> personality category=Neuroticism 168 <conf:(1)>
6. personality category=Neuroticism 168 ==> Performance=Low 168 <conf:(1)>
7. personality category=Neuroticism Performance=Low 168 ==> Learning category=Theorist 168 <conf:(1)>
8. Learning category=Theorist Performance=Low 168 ==> personality category=Neuroticism 168 <conf:(1)>
9. Learning category=Theorist personality category=Neuroticism 168 ==> Performance=Low 168 <conf:(1)>
10. Performance=Low 168 ==> Learning category=Theorist personality category=Neuroticism 168
11. personality category=Neuroticism 168 ==> Learning category=Theorist Performance=Low 168 <conf:(1)>
12. Learning category=Theorist 168 ==> personality category=Neuroticism Performance=Low 168 <conf:(1)>
13. Learning category=pragmatist 108 ==> personality category=Extraversion 108 <conf:(1)>
14. Learning category=pragmatist 108 ==> Performance=Average 108 <conf:(1)>
15. personality category=Extraversion Performance=Average 108 ==> Learning category=pragmatist 108 <conf:(1)>
16. Learning category=pragmatist Performance=Average 108 ==> personality category=Extraversion 108
1

Table VI reveals the best association rules discovered. It shows the strong association between Learning Style, Personality and Performance with confidence 1.

## V. CONCLUSION

In this paper, Association between Personality, Learning Style and Academic Performance is discovered by employing Model based clustering technique and Multilayer Perceptron. The students are grouped under the category of learning styles (Activist, Theorist, Pragmatist, and Reflector), Personality Traits (Extrovert, Introvert, Psychoticism) and Performance Scale (High, Average and Low) using effective clustering. The classifier reveals that each individual student's Learning Style is associated with his/her Personality and Performance. Hence the following observations are made, Theorist Learners are neuroticism personalities and their performance scale is low. Reflector Learners are Introverts and their performance scale is average. Pragmatist Learners are Extroverts personality and their performance scale is average. Some of the extrovert personalities are Activist Learners with high performance scale. The Correlation analysis divulges that there exist strong association between the Learning Style, Personality type and Performance.

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