International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 10, No.1 (Oct.-2021)

http://dx.doi.org/10.12785/ijcds/100188

Model for Analyzing Psychological Parameters Recommending Student Learning Behaviour using Machine Learning

Iti Burman [1], Subhranil Som [2] and Syed Akhter Hossain [3]

[1] Department of Information Technology, Vivekananda Institute of Professional Studies, India
[2] Bhairab Ganguly College, Belgharia, Kolkata, West Bengal, India
[3] Daffodil International University, Dhaka, Bangladesh

Received 16 Mar. 2020, Revised 22 Jul. 2021, Accepted 05 Aug. 2021, Published 28 Oct. 2021

Abstract: One of the main objectives of Educational Data Mining (EDM) is to improve the education system to increase student retention, help students to score high and attain holistic development. The purpose of the study is to analyze the psychological parameters of students to predict their intellectual performance and generate recommendations to be utilized by institutes and students to improve academic performance. This study performs matrix factorization using single value decomposition (SVD) to predict missing parameters related to the psychological behaviour of students with root mean square equals 0.059 and uses the user-based collaborative filtering technique to predict their grade with RMSEA as 0.055. It makes use of decision tree (ID3) algorithm for generating decision rules that produces results with an accuracy of 76% and provides suggestions on how to improve learning by changing the psychological behaviour of students. The results showed that three parameters of personality (namely conscientiousness, openness and need for cognition), six of motivation construct (intrinsic motivation, optimistic, goal orientation, concentration, locus of control and self-efficacy), five of self-regulatory learning strategies construct (rehearsal, elaboration, meta-cognition, peer learning, time/study management) highly impacted academic performance in positive way. Students belonging to upper and middle socioeconomic status avail more from learning facilities. Also, learning the in-depth knowledge of the topic enhance student intellectual performance. It is noted that social integration and academic integration help students to learn the subject matter in friendly environment and reduces depression. The key findings highlight the parameters positively impacting students' intellectual performance. This help in improving students' intellectual performance which further addresses student retention, progress and employability.

Keywords: Academic Performance, Single Value Decomposition, Student, Educational Data Mining, Prediction, Recommendation, Collaborative Filtering, Decision Tree

1. Introduction

Student's intellectual performance is an enduring issue for institutes, students and society as education is essential for the growth of any country. Education has also progressed with the advancement in technology. Online resources have eliminated the barriers related to absenteeism in the classroom and face to face teaching-learning process. Besides various tutorials, educational websites and availability of subject material all the time it is noted that the performance of students is not satisfactory. Since, students differ in their behaviour and academic competencies the need to study various parameters affecting the academic performance of students is a matter of important concern. This laid the foundation for comprehensive research on enhancing student academic performance with the use of their academic and non-academic abilities.

Timely prediction of the academic and non-academic performance of student can help institutes to identify the areas a student is lacking and can beforehand improve it by taking necessary actions. It is evident from previous studies that non-intellectual constructs of students significantly impact their academic performance. Various data mining techniques such as linear regression [35], logistic regression [18], neural networks [63], support vector machine [73], decision tree [75] have been extensively studied for predicting the aforementioned objective. Romero, Ventura, Espejo and Hervás (2008) [63] classified students to predict their marks based on

E-mail: itiburman0017@gmail.com, subhranil.som@gmail.com, aktarhossain@daffodilvarsity.edu.bd

usage of Moodle courses. It helps in determining activities that help students to attain high marks and to eliminate those which are related to low marks. It also assists teachers in identifying problems related to the learning of students and could provide them with solutions on time. It has been noted that the techniques matrix factorization using factorizing machine (FM), multilinear regression and random forests produce lower error rates than previously applied techniques [71].

The work carried in [37] focused on academic parameters including a deadline of assignment submission, time of admission, attendance in the classroom on daily basis, giving examination on scheduled date and time, to predict the academic performance of undergraduate and graduate students. Personality traits of individuals' impact their intellect [55]. Also, parameters of self-regulatory learning strategies (SRLS) and motivation are highlighted in recent years [3]. SRLS has become an important skill in the current period and both SRLS and motivation are not part of classroom learning which makes them an essential aspect of learning [21]. Moreover, students who lack SRLS, motivation and cognitive abilities face academic challenges [9, 14, 27]. Students residing in rural areas having low socioeconomic status lack in motivation skills and have incompetent interpretations [15]. Students' learning style comprise of cognitive abilities, emotions and psychometric parameters which describe the ways students react to the learning environment and the learning environment impacts the academic performance of students [17].

Recommender systems are used extensively in various areas [58] helping businesses and users in different ways. Its application can be found in envisioning the performance of students in a timely and accurate manner. An approach of the recommender system has been proposed to predict the academic performance of students [74]. The recommendation approach is also used in e-learning to enhance technology-based learning [47]. The objective of such a system would be to recommend learning resources to the students to enhance their learning [36].

Various methods have been applied for generating recommendations in electronic commerce [6]. It includes asymmetric factor models, regression models, restricted Boltzmann machines with gaussian visible units, restricted Boltzmann machines, matrix factorization and neighborhood-based model (k-NN) for movie recommender system. Broadly these methods are categorized into content-based or collaborative filtering-based techniques. Both the methods commonly require a rating matrix for prediction. Also, content-based technique requires the profile of users, description of items, or both. Sweeney, Rangwala, Lester and Johri [71] proposed a hybrid method combining the features of factorization machines and random forests to predict the grades of students. It uses demographic features, features defining course and performance record of students, for prediction. To improve student retention Elbadrawy et. al. [31] has proposed a personalized recommendation approach using matrix factorization and multi regression. For analysis, it involves current grades of students, features of activities, courses and learning management system, and MOOC data of Stanford. Besides various researchers worked for improving education system by exploring distinct parameters and different techniques, there exists a scope to revive the education system as population is vast and the problem of unemployment exists. Moreover, education system needs revival from time to time to meet the dynamic needs of industry. Also, with the change of era and advancement of technologies student's behaviour changes and hence it needs to be analyzed from time to time. With this viewpoint, the study here includes students, their psychometric parameters and performance in terms of their scored marks. It proposes an approach to predict the values for unfilled psychological parameters of students based upon the given parameters, predicts their academic performance and generating recommendations on how to improve the academic performance of students.

The organization of the paper is as section 2 describes the related work and discusses about various parameters involved in analysis; section 3 describes research methodology and focus on the analysis part; results findings and interpretation are discussed in section 4; section 5 provides a conclusion and implications of research and finally section 6 defines limitations and future scope.

2. RELATED WORK AND PSYCHOLOGICAL CONSTRUCTS

Students differ in their psychological behaviour and it can be utilized to predict their academic performance. The differences in cognitive skills of students, referring to mental abilities to interpret and understand the subject matter, result in variation in their academic performance [59]. The study in [16, 41] describes the individuals' intelligence in terms of their psychological nature and focused on how these can be most effectively assessed. Literature shows that numerous non-intellectual parameters have been identified associated with the academic performance of students. The study in [55] shows the association of personality factors with the academic performance of students. Also, the relationships between personality, interest, and intelligence are depicted by Ackerman and Heggestad [1]. It has been found that motivational factor, self-regulatory learning strategies and learning style; also contribute to the academic performance of students [19, 61].

The research shows that non-intellectual parameters influence the intellectual performance of students and identification of those non-intellectual parameters hence becomes an important task. Various studies assessed the personality traits of students to explore their effect on the academic performance of students [55]. Further, it has been noted that conscientiousness constructs estimated 72 percent [60]. Researchers also highlighted that objectives and beliefs related to performance are changing and strategies associated with learning can be adjusted to bring under control in order to enhance learning [29]. The study in [86] stated that the students who are self-monitored learners engage actively in tasks in terms of motivation, metacognition, and behaviourism. This implies that frameworks for academic performance have to include constructs related to motivation, self-monitored learning, performance goals and expectancies [30, 61].

Based on the literature and previous work, the study here includes six major non-intellectual constructs impacting the academic performance of students which include traits of personality, factors affecting motivation, self-monitored strategies for learning, psychosocial contextual influences, demographics and learning approach. These constructs are further categorized as depicted in Table I.

TABLE I. NON-INTELLECTUAL PARAMETERS FOR STUDENT ACADEMIC PERFORMANCE

Personality traits	**Motivational Factors**	**Self-Regulatory Learning Strategies**	**Approach Towards Learning**	**Psychosocial Contextual Factors**	**Demographics**
Conscientiousness	Locus of control	Anxiety	Deep	Social integration	Socio economic status
Procrastination	Pessimistic	Rehearsal	Strategic	Academic integration	
Openness	Optimistic	Concentration	Surface	Stress	
Neuroticism	Self-efficacy	Elaboration			
Agreeableness	Goal orientation	Critical thinking			
Extraversion	Intrinsic motivation	Metacognition			
Need for cognition	Extrinsic motivation	Effort regulation			
		Help-seeking			
		Peer learning			
		Time/Study management			

A. Personality Traits

The well-known model for personality known as the five-factor model with constructs conscientiousness, openness, neuroticism, agreeableness, and extraversion; gives an exhaustive approach to assess personality [22]. These five constructs are useful in predicting the academic performance of students [55]. Conscientiousness measures the degree of organization and ambition of an individual. It has been seen that students with high degree conscientiousness perform well in academics [49]. Procrastination is another personality construct defined as an individuals' behaviour to delay the tasks [48]. This behavioural tendency of postponing decision-making limits self-monitoring and leads to negative conscientiousness [69]. Students with high procrastination face problems in dealing with challenging tasks.

Students who are imaginative and practice new ideas, i.e. those who are high in openness practice new learning elements and able to score high marks in academics [77, 83]. It has been seen that students with a high level of agreeableness cooperate with their instructors and enhance the learning process [77]. Extraversion is defined as a behaviour where an individual is more socially active, interacts and tries to know about others. This can cause distraction in students easily and suppress their learning resulting in lower academic performance [62]. Students with a high level of anxiety and/or fear suffer neuroticism and are not able to perform well in examinations [53]. Also, the construct 'need for cognition' [56] positively impact academic performance and reflects higher intrinsic motivation which inspires students to engage in effortful intellectual processing.

B. Motivational Factors

Various theories of motivation exist [30] comprising of distinct constructs but out of these only a few constructs are used repeatedly for the academic performance of students. The way individuals describe causation is referred to as attributions [38, 52] and for students, it is related to their past academic failures. Some students take it as their responsibility for failing in the set objective whereas others try to find out external factors for it. This is termed as the locus of control [43]. The pessimistic behaviour referring to negative thoughts in students' minds leads to lower grades. On the other hand, optimistic behaviour leads to higher grades as it is associated with positive outcomes and strong motivation [12].

Self-efficacy here refers to student skills and abilities in academic subjects. It has been noted that those who are positive towards their efficiencies score high in academics in comparison to their counterparts [5]. Students who are goal-oriented focus on self-improvement and achievements which affects their motivation and academic performance. The theory of self-determination [65] differentiates motivation as intrinsic and extrinsic. Students engaging in tasks for enhancing their learning, efficiencies are intrinsically motivated and perform well in academics. In contrast, those who seek rewards for tasks or engage in activities to avoid punishment are extrinsically motivated. Extrinsic motivation stifles the academic performance of students and leads to volitional difficulties [24].

C. Self-Regulatory Learning Strategies

Students control their understanding, cognitive skills, surrounding and motivation behaviour [11]. Self-regulation focuses on the implementation of student efforts in the best possible way to succeed in academics. Therefore, evaluation of these strategies facilitates in envisioning the academic performance of students in a more accurate manner [82]. The self-regulated learning model given by [54] assesses the strategies related to learning with (MSLQ) Motivated Strategies for Learning Questionnaire. It includes elaboration, critical thinking, metacognition, rehearsal, peer learning, and time/study management. Rehearsal refers to learning through repetition, elaboration where students summarize the contents in their own words, critical thinking referring to skills to examine analyze and solve problems, metacognition refers to regulatory techniques involving planning, flexibility, and self-monitoring. Pintrich, 2004 [54] assesses effort regulation under self-regulatory capacities. It refers to managing motivation or persistence, especially when faced by difficult tasks. Peer learning involves learning by sharing knowledge with peers. Time/study management improve performance of students with the help of proper study schedule and regulating learning environments. Help-seeking refers to a behaviour where student seeks help from their instructors or peers. The Learning and Study Strategy Inventory (LASSI) also assesses concentration in addition to the strategies measured in MSLQ. Concentration is the capability of a student to maintain their attention and focus while studying. The above strategies facilitate deep learning and academic achievement. Anxiety is another strategy that may negatively impact academic performance. It refers to the thought of fear or pressure and this may lead to difficulties in learning which deviate students from their goals.

D. Students' Approach Towards Learning

Different approaches to learning have been identified [7, 42, 34] comprising of deep, strategic and surface learning. Deep learning is defined as an approach where students are intrinsically motivated and utilize their cognitive skills to learn the concept. In contrast in surface learning, students learn through repetition or rote learning with extrinsic motivation to pass the examination. Strategic learning can be defined as a combination of the two. In this approach, students follow deep or surface learning approaches depending upon the task importance and characterization.

Distinct approaches to learning have a direct effect on student learning and contribute to predicting the academic performance of students [28]. Various studies found a relationship of approaches to learning with student's academic achievement. Generally, it is found that deep learning and strategic learning approaches contribute positively to the academic achievement of students. Also, in the study by Sadler-Smith [66] and Newstead [50] it was found that strategic and deep approaches are positively correlated to the academic performance of students. Entwistle, Tait and McCune, [33] suggested the surface and strategic learning approaches for undergraduate students studying fact-oriented subjects. He also found that a positive relationship exists between deep learning approach and academic success in graduate students. With this reference, it is important to examine the relationship between different approaches to learning and academic success of students.

E. Psychosocial Contextual Influences

The study in [76] focused on student retention. Tinto's academic endurance model stated that institutions itself manifest the withdrawal behaviour of students. The model concludes that institutions interact with students through their characteristics and past achievements to know the extent to which students interact with the academic system and peers. The information can be utilized to build strong institutional, academic and social integration which facilitates student retention and academic achievement. Tinto [76] stated that students need to be socially integrated i.e. to involve themselves in a culture of students, outside and inside the actual background of the learning environment, in addition to academically integrated i.e. to pursue in their study to obtain a graduate degree. The parameters defined in Tinto's study have been validated empirically when applying to various educational institutes support varied [84, 46]. As an illustration, it has been found that students studying in distinct courses in different academic years' experience different levels of social and academic integration [46].

Students who feel comfortable and are amiable with their class fellows and instructors and actively participate in extra-curricular activities are likely to persist in their graduation degree [67]. The social network of students i.e. supports by family and friends positively affect the study-achievement of students of first-year [80]. In addition to the interaction model of Tinto, Baker and Siryk [4] observed that academic and social integration influence the study performance of students.
Stress affects the academic performance of students and may lead to depression. Educational institutes have students coming from diversity. In a study of international students, it has been identified that 41% of them experience stress due to unfamiliar environment, alienation and favoritism [64]. It is more difficult for outside students to cope with the social and academic environments as compared to domestic students. Hence, international students require additional effort and concern towards social integration [10, 85]. External factors like support from family and earning from employment influence integration [32, 70]. These factors also affect the student responses related to stress towards their institutional life.

F. Demographic

The student population in the university is diverse and this results in exploring the impact of demographics on their academics. It has been noted that students belonging to higher socioeconomic backgrounds obtain high grades in comparison to their counterparts [61, 26, 68]. This raises the need to study the effect of demographics on student academic performance.

After extensive literature review it has been noticed that students' academic performance is affected by their non-intellectual parameters in addition to their intellectual parameters. It requires extensive analysis of the parameters to improvise the education system and academic achievement of students. Most of the studies focused on only few parameters except by Richardson, Abraham and Bond [59], and no conclusion regarding the collective effect of all parameters has been drawn. No study focussed on how a model comprising of all the parameters will assist academic achievement of students in Indian scenario. Previous studies were more focused on predicting intellectual performance of students at school and tertiary level. The researchers make use of various classification techniques of data mining and machine learning techniques to predict the academic achievement of students. A handful of the proposed studies aimed at generating suggestions on improving student retention, assisting admission process and recommending course material. But no study considered all the factors to generate recommendations on how to improve the learning behaviour and thereby academic performance of students and predicting psychological behaviour of students.

3. Research Methodology

This section demonstrates the model as depicted in Fig. 1 and describes the procedure of generating items, data collection, and analysis.

A. Generating Items and Data Collection

After extensive literature of constructs, 75 statements were formed. The domain of the constructs has to be covered to enhance validity [20]. To do so, the study analyzed all the statements covering all the items discussed in section 2. It was further reviewed by a psychology expert and a doctoral student for a pre-pilot study. For the pilot study, a sample of data from a hundred students has been collected from three randomly selected colleges affiliated from GGSIP University. Students were also randomly selected studying distinct courses. The data from the students was collected using identified statements for further analysis. During pilot study, factor analysis was performed on sample data and it was found that 12 statements were not loaded in any of the factors. The remaining statements were selected to prepare a structured questionnaire to collect data for analysis. The questionnaire intends to collect the data about student psychological behaviour affecting their academic performance. Cronbach alpha value is measured to check the internal consistency of the items or reliability which values 0.89.

Graduation is a very important phase in students' life since it will lay a direction for their future studies or career. The study here hence focuses on undergraduate final year students. Probability sampling has been used to choose the respondents. The study first prepares a list of colleges affiliated to universities running different courses and out of these 11 colleges are randomly selected. Target students are then selected randomly from those colleges to facilitate the collection of data. The interviewer recorded their responses on a scale ranging from 1(strongly agree) to 5 (Strongly disagree). Since the data comprise of the students studying heterogeneous courses hence the study is extensive. For the construct approach towards learning, the responses are recorded in the categorical form of data. The data is collected in a large number from 2198 students. Out of those observations 187 were found biased and dropped. The final size of the sample is then 2011 which is justified statistically according to the nature of the study [44].

B. Data Representation and Normalization

The psychological dataset can be represented in matrix form and mapped as a student, psychometric parameters and performance to user, items and rating respectively as depicted in Table II.

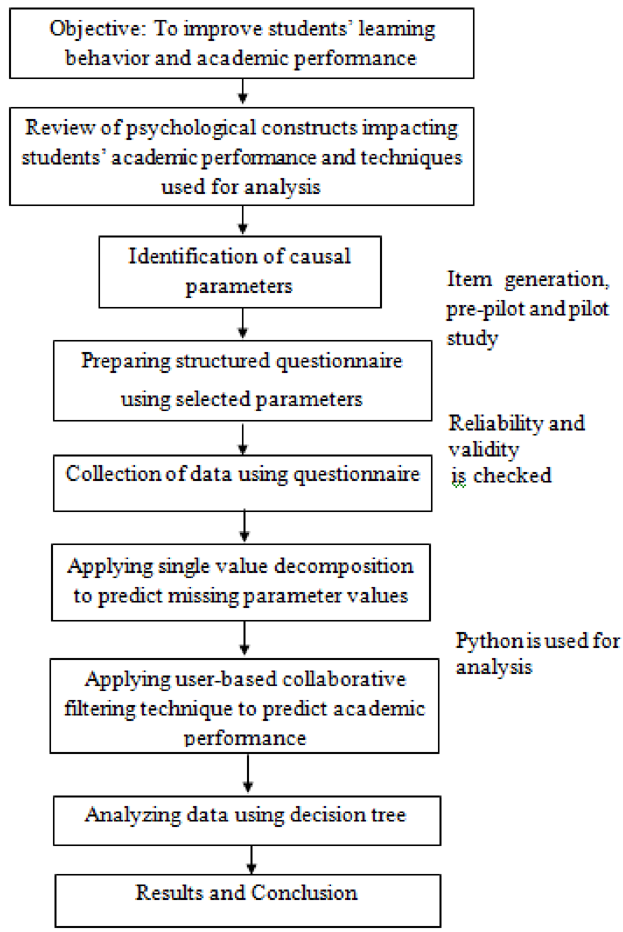

FIGURE 1. RESEARCH MODEL

TABLE. II. DATA REPRESENTATION

Parameters/ Students	**P1**	**P2**	**P3**	**…**	**Pn**	**Target Grades (y)/ Academic Performance**
S1	3	5	1	…	2	8
S2	4	3	5	…	4	7
…	…	…	…	…	…	…
Sn	1	2	3	…	2	8

The rows represent students (S1…Sn) and columns represent various psychometric parameters from P1 to Pn (x) of students with their academic scores (y). Each cell represents a value between 1 (strongly agree) and 5 (strongly disagree). This matrix representation of data helps in analyzing data for recommendation purpose. The data is normalized using scaling to the unit method in which x_{norm} equals observation divided by the euclidian length of the feature vector [2].

C. Single Value Decomposition

Any given matrix $X_{m,n}$ can be decomposed into three matrices U, ∑ & V^T such that the elements of X represented as x_{ij} can be expressed as

$$x_{ij} = U_{1i}\sum_1 V^T_{1j} + U_{2i}\sum_2 V^T_{2j} + \ldots + U_{ri}\sum_r V^T_{rj} \quad (1)$$

where U and V^T are orthogonal matrices and ∑ is a non-negative diagonal matrix. This is referred to as single value decomposition. The rank of matrix X is the number of terms i.e., r in (1) and its value cannot be increased by m or n whichever is less. A cell of original matrix X can be computed by multiplying the corresponding elements of three matrices U, ∑ & V^T and then adding all the obtained terms. X can be represented in matrix notation as

$$X_{mxn} = U_{mxr} \ \sum_{rxr} \ V^T_{rxp} \quad (2)$$

SVD has various applications particularly in detecting and treating collinearity and near collinearity in multiple linear regression, analyzing experimental designs, evaluating two-way tables and empirical fitting of functions [45]. Apart from these, its application can be seen in recommender systems for predicting the ratings or missing values. The study in this paper makes use of SVD to predict the missing values of student parameters related to their psychometric behaviour affecting their academic performance. The matrix (x) consisting of data related to psychological parameters of students is decomposed into u, sigma and v' matrices using SVD. The missing values of a student can then be predicted as:

$$new\_user = new\_user\_data\_vector * sigma * v' \quad (3)$$

D. Collaborative Filtering Technique

This technique of recommender system works on users' past preferences on a set of items to predict items of their interests. It is categorized as user-based collaborative filtering and item-based collaborative filtering. The collaborative filtering technique has been used by O'Mahony & Smyth [51] to develop a recommender system for suggesting courses for Dublin University college students to enhance online module selection procedures. It provides information about enrolment requirements of university students and identified factors influencing the selection of modules. User-based collaborative approach finds the students who are similar to the target student based on their psychological parameters whereas item-based collaborative filtering considers a parameter, finds students whose behaviour matches that parameter and will identify other parameters that those students have in their behaviour. The study considered both methods and it was found that item-based collaborative approach is not suitable and hence user-based collaborative filtering is used. Item-based collaborative approach suffers from various limitations. First, limited content analysis i.e. content may not be easily extracted. Second, it lacks diversity and third, it suffers from the cold start problems for the new users. In this, the technique is used to predict the grades of students. Various studies worked on different set of students' psychological parameters using distinct techniques. It is noted from literature that no research considers all psychological parameters to predict students' academic performance and uses user-based collaborative filtering technique. Given a pxq matrix of data of students, with students s_i, i=1,2,…,n; their psychological parameters p_j, j=1,2,…,n.; and the value at each row and column intersection depicts the psychological behaviour of students. To predict the grade of a student S, it first searches for a student s_i for some value of i, whose psychological behaviour nearly matches with S. The study here considers two methods of user-based collaborative filtering approach, pearson correlation and cosine similarity, to identify the student from given set of data. The similarity between two students, x and y, using pearson correlation, $r_{x,y,}$ can be computed as:

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - x')(y_i - y')}{\sqrt{\sum_{i=1}^{n}(x_i - x\prime)^2}\sqrt{\sum_{i=1}^{n}(y_i - y\prime)^2}} \quad (4)$$

where x' and y' represent mean of x and y respectively.

The cosine similarity between two students, x and y, is computed as:

$$\text{similarity(x,y)} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} {x_i}^2}\sqrt{\sum_{i=1}^{n} {y_i}^2}} \quad (5)$$

E. Decision Tree Algorithm

The decision tree is a classification technique of data mining and in real life, it has various analogies that influence its use in machine learning. It represents decision rules and aid decision making with the construction of tree-like structure. In the study by Dekker, Pechenizkiy and Vleeshouwers [25] decision tree classifier is used to anticipate the student drop in electrical engineering course. Another application of a decision tree is found in [39] which is used to plan courses. The present study applies machine learning using ID3 algorithm of decision tree. The study considers various parameters and it helps in exploring various aspects of such complex problems. It classifies students as high, average and low scorers based on their scored marks in previous assessments. It assists in enhancing learning behaviour of low scorers by identifying the psychological parameters leading to low performance and suggesting ways to improve it.

To implement the above steps to predict and classify the students, python is used. For validation of the decision tree, 10-fold cross-validation is performed where data is divided into 10 equal parts. Nine out of ten of those parts are used for training and one for testing, and this procedure is repeated with every part as a test case.

4. Results Findings And Interpretation

Multiple fit indices are available to measure the fit of any model. The effectiveness of the prediction using single value decomposition and the collaborative filtering approach is evaluated using root mean square error (RMSEA). A value between 0.05 and 0.08 is acceptable for RMSEA [13]. The book by Browne, Cudeck, Bollen and Long [13] provides information for testing structured equation models. Also, it gives practical knowledge for multivariate analysis, multivariate normality and provides fit indices. It was found that the missing psychometric parameters of students are predicted using SVD with a root mean square of 0.059. The grades of students have been predicted using pearson correlation and cosine similarity methods of collaborative filtering approach. It has been noted that cosine similarity produces more accurate results with RMSEA as 0.055 in comparison to pearson correlation with RMSEA as 0.061. ID3 algorithm is used for classification. The result of accuracy and result validation indicator is shown in Table III. Class precision is described as the percentage of well anticipated, *i.e.* true positive and false negative. The class recall is described as the percentage of well-defined components. The accuracy can be defined as the ratio of truly classified to the total number of instances. The total classification is calculated as the sum of true positive and true negative [81]. The study in this paper results in 76% of the classification accuracy such accuracy level is acceptable in study related to social sciences [72]. F1 score method is used to measure the validity of results and it is defined as the harmonic mean of class precision and class recall. F1 score in the present study is found as 71% for average class, 81% for high class and 57% for low class.

Table. III. Result of classification

	Precision	Recall	F1 – Score
Average	0.85	0.61	0.71
High	0.72	0.93	0.81
Low	1.00	0.40	0.57
Macro average	0.89	0.65	0.70
Weighted average	0.79	0.76	0.75

The decision about the psychometric variables so that they result in enhanced performance can be obtained from the decision tree. The ID3 algorithm is used for creating a decision tree. It was developed by J. R. Quinlan [57] and is used extensively in various domains for decision making. It uses information gain and entropy for the construction of decision trees. The path from the root of the tree to the leaves will help in identifying the rules by following which students can enhance their academic performance.

The algorithm uses gini index to split the tree. Here it is used to measure the degree of a randomly selected psychometric parameter being wrongly classified. It values between 0 and 1, where a value 0 depicts that all students with this parameter belong to only one class, and a value 1 depicts that the students are randomly distributed across all three classes. The decision rules related to parameters contributing to high marks with 0 or near to zero gini index value are obtained using decision tree as follows:

Learning approach <= 1.5
| Conscientiousness <= 2.5
| | Self efficacy <= 1.5
| | | Extraversion <= 3.5
| | | | Socioeconomic status <=2.5
| | | | | Help seeking <= 1.5: High
| | | | Critical thinking <=2.5
| | | | | Optimistic <=2.5: High
| | | | | Agreeableness <=1.5: High
| | | Socioeconomic status <=2.5
| | | | | Openness <=2.5
| | | | | | Critical thinking <=2.5
| | | | | | | Neuroticism <=4.5: High
| | | | | Rehearsal <=1.5
| | | | | | Stress <=3.5
| | | | | | | Goal orientation <=2.0: High
| | Procrastination <=1.5
| | | Rehearsal <= 2.5
| | | | Optimistic <=2.5
| | | | | Critical thinking <= 1.5
| | | | | | Locus of control <=4.0: High
| | | | Self efficacy <=4.5
| | | | | Peer learning <= 2.5
| | | | | | Time/Study management <=3.5:High
| | | | | | Intrinsic motivation <=4.0: High
Learning approach > 1.5
| Openness <= 3.5
| | Metacognition <= 2.5
| | | Self efficacy <=2.5
| | | | Anxiety <=2.5
| | | | | Goal orientation <= 4.5: High
| | | | | Need for cognition <= 3.5: High
| | | | | | Time/Study management <=1.5: High
| | | Effort regulation <=2.5
| | | | Academic integration <=4.0
| | | | | Procrastination <=3.5: High
| | | | Need for cognition <=3.5
| | | | | Goal orientation <=1.5
| | | | | | Peer learning <=3.5: High
| | Socioeconomic stauts <=1.5
| | | Social integration <= 2.5
| | | | Learning approach <= 2.5
| | | | | Concentration <=1.5: High
| | | | Conscientiousness <= 2.5
| | | | | Locus of control <=3.5
| | | | | | Anxiety <=3.5: High

From the above rules, it has been noticed that the constructs - learning approach, openness, meta-cognition, self-efficacy, anxiety, need for cognition, time/study management, effort regulation, peer learning, and goal orientation are important to be in the class with high marks.

The decision rules stated are a description of the decision tree diagram obtained using ID3 algorithm. The decision tree is depicted in different parts from Fig. 2 to Fig. 15 to provide clear view. Although the decision tree classifies students into three classes: High, Average and Low, the rules of the decision tree depict the parameter values to enhance the academic performance of students. The values between 1 and 2 describe the positive engagement of psychometric construct with academics of students, a value near to 3 show impartial effect and values near to 4 and 5 depicts the least contribution in academia. For construct student approach towards learning a value 1 or near to 1 depicts deep learning, 2 depicts strategic learning and 3 depicts surface learning. Similarly, for construct demographics value 1 or near 1 depict upper socioeconomic status, 2 depict middle socioeconomic status and 3 depict lower socioeconomic status.

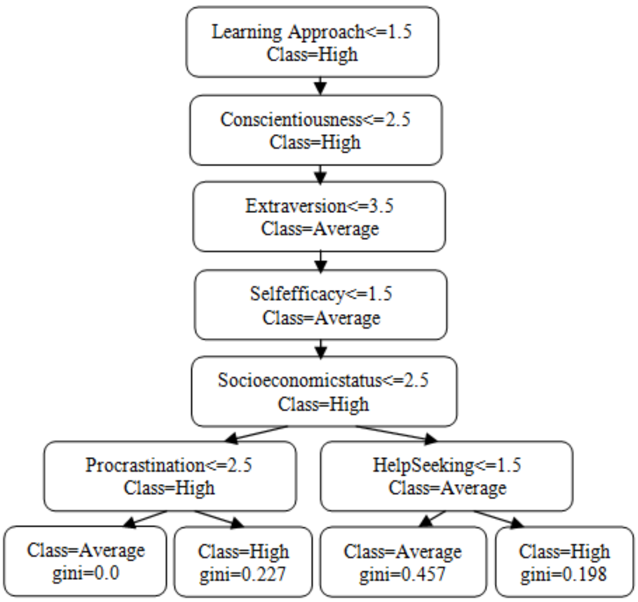

FIGURE 2. DECISION TREE PART 1

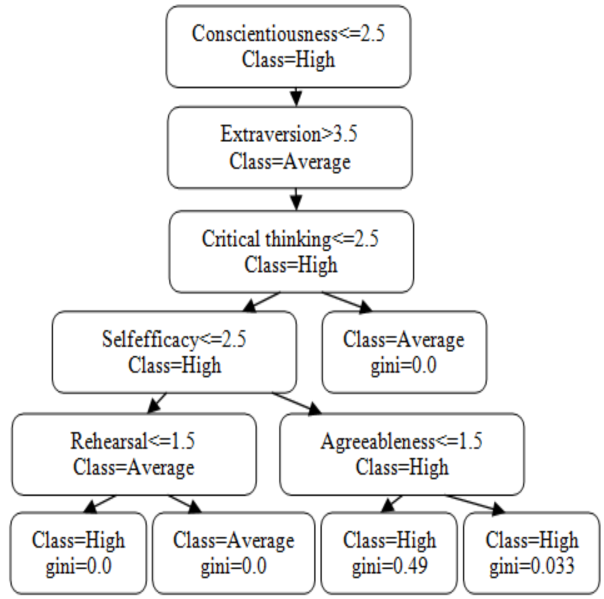

FIGURE 4. DECISION TREE PART 3

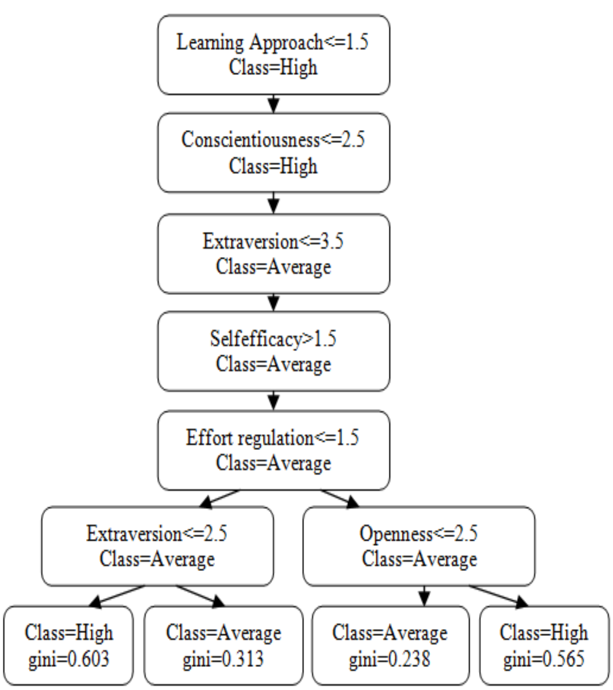

FIGURE 3. DECISION TREE PART 2

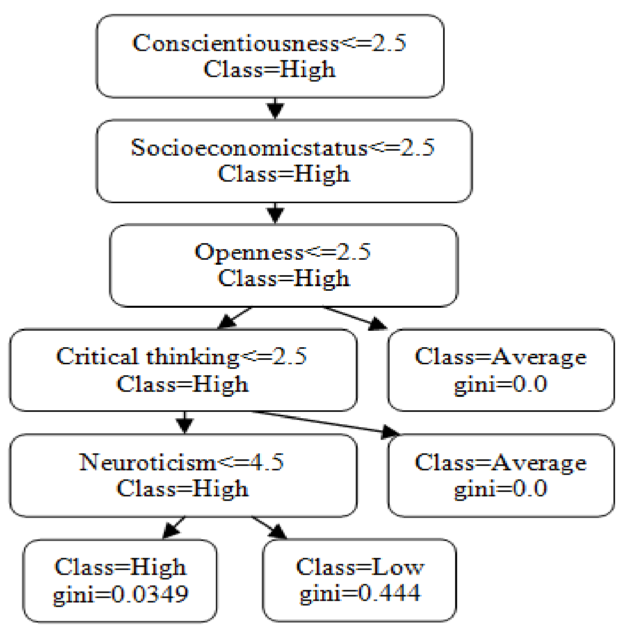

FIGURE 5. DECISION TREE PART 4

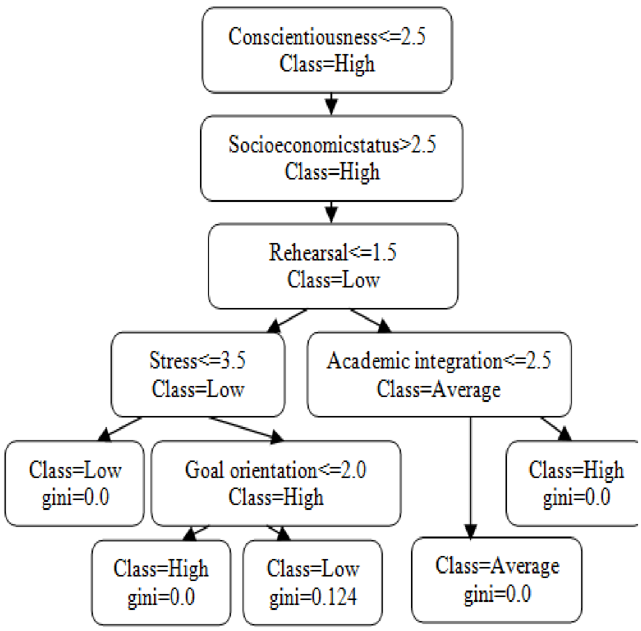

FIGURE 6. DECISION TREE PART 5

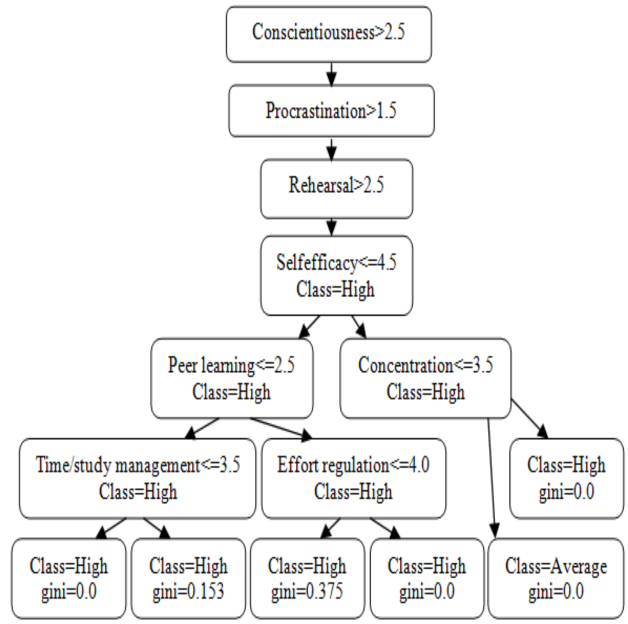

FIGURE 8. DECISION TREE PART 7

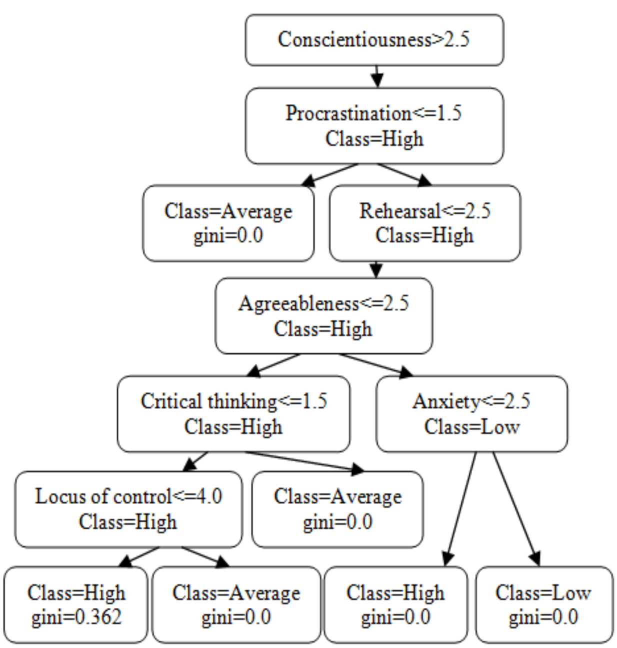

FIGURE 7. DECISION TREE PART 6

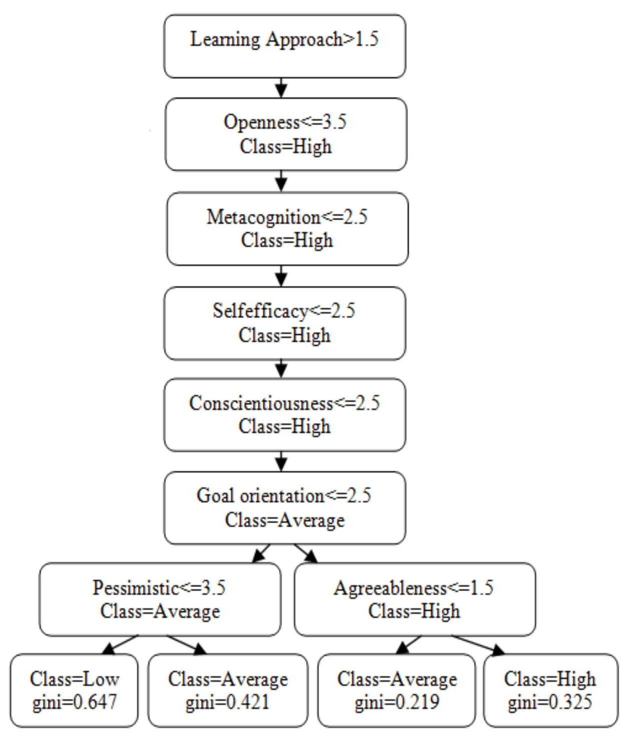

FIGURE 9. DECISION TREE PART 8

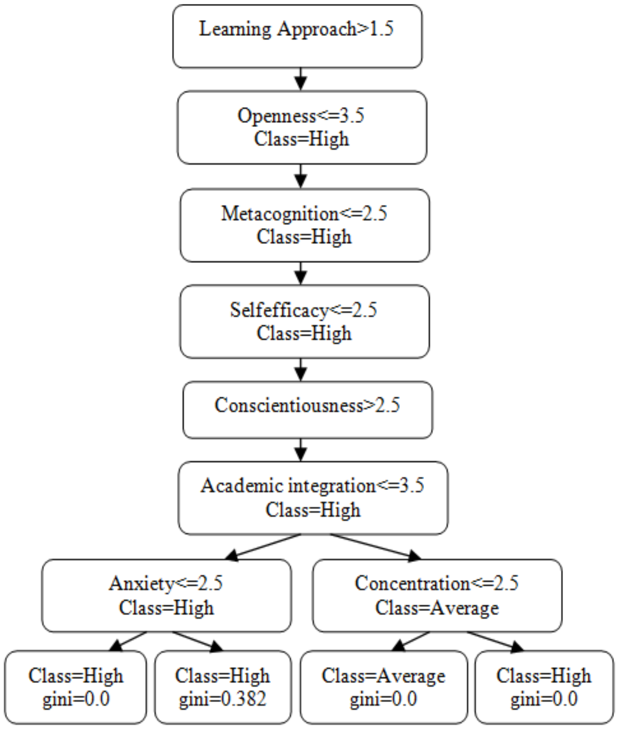

FIGURE 10. DECISION TREE PART 9

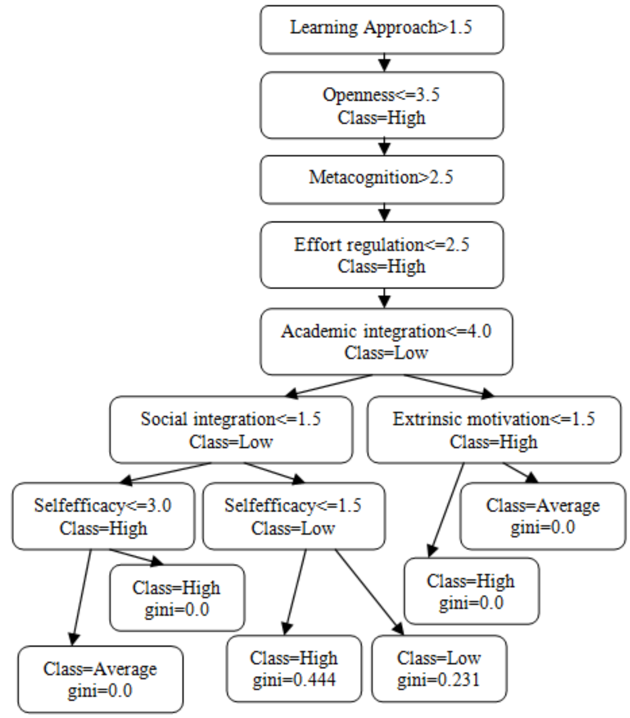

FIGURE 12. DECISION TREE PART 11

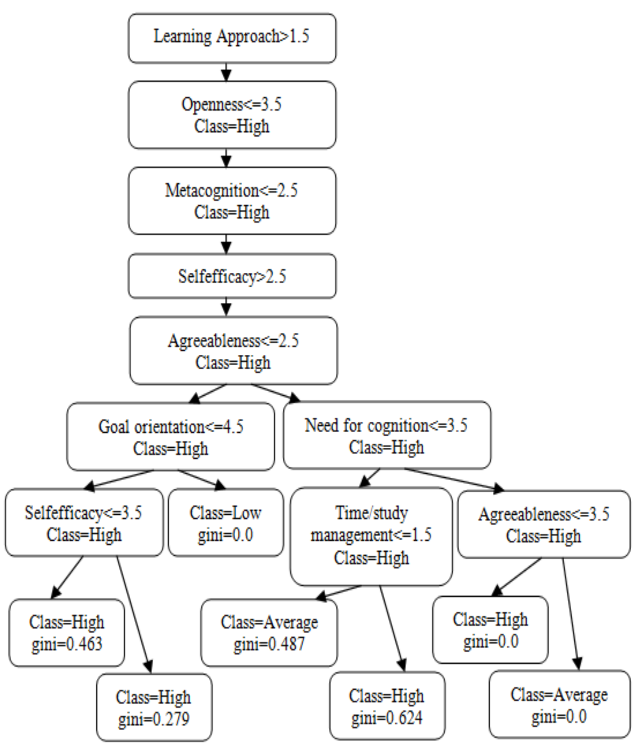

FIGURE 11. DECISION TREE PART 10

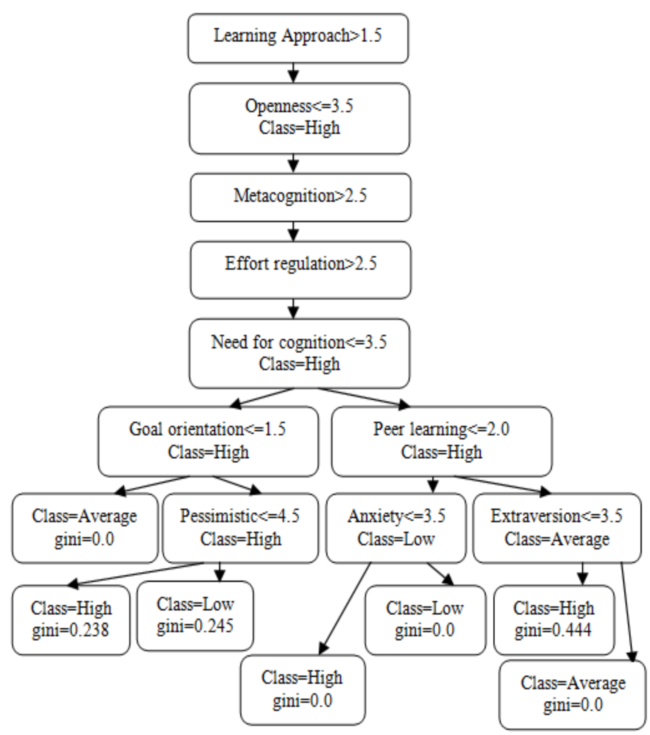

FIGURE 13. DECISION TREE PART 12

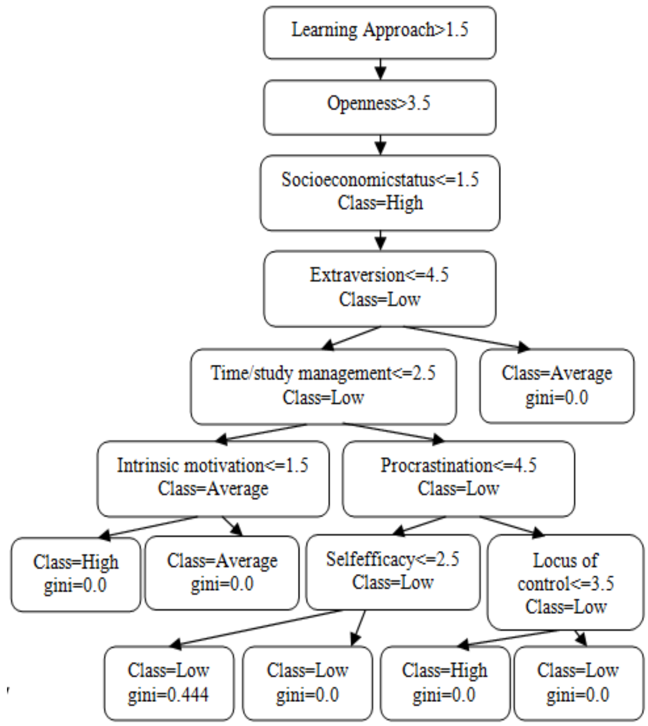

FIGURE 14. DECISION TREE PART 13

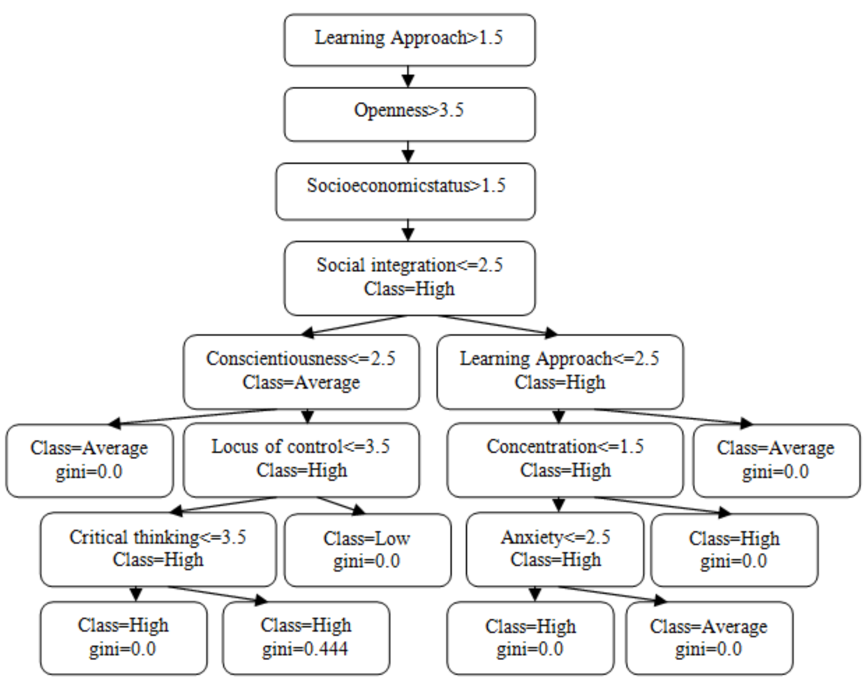

FIGURE 15. DECISION TREE PART 14

5. Conclusion And Implications Of Research

The paper focuses on different psychometric parameters of students impacting their academic performance and learning behaviour. The main objective of the study is to identify the parameters positively contributing to the academic success of students and those which negatively contributes to academic success. The study make use of three techniques namely single value decomposition (SVD), user-based collaborative filtering approach and ID3 decision tree algorithm to achieve the objectives of the study. The RMSE value has been used as measurement metric for SVD and user-based collaborative filtering approach which equals 0.059 [13] and 0.055 [13] respectively. The classification accuracy of ID3 algorithm has been found to be 76% [72]. Table 4 discusses various key findings of the study. The study predicts the behaviour of the students by analysing various parameters including personality, motivation, self-regulation strategies for learning, psychosocial contextual influences, approach towards learning and demographic, by leveraging industry linked data, academicians, past precedence, surveys and based on multiple studies conducted by researchers across globe in multiple sub components of this study. The basis of these data set includes industry defined curriculums and best practices. The references of the studies are considered while preforming this analysis subsequently references during the various papers referred during the analysis. Although the study outcome will become basis and support while define industry standards, curriculum, framework and delivery methods. The analysis will become base and will help industry to further define parameters and build models which will help defining various research objectives. As the model helps in enhancing learning behaviour of students, it will help students in perceiving industry related curriculum and projects in a more understandable and pragmatic manner. The model help instructors in examining the areas where students lack and they can adopt various strategies to enhance teaching-learning process. By examining the skills of the students, instructors can assign the industry-linked curriculum and projects to the students that help in enhancing their cognitive skills and abilities, solving problems related to unemployment and improves pedagogy. The study majorly contributes to enhancing the intellectual performance of students which further improvise employability, help in student's retention and benefit students, institutes and society in large. The decision rules help in finding the parameters leading to enhancement in academic scores and learning of students.

TABLE. IV. KEY FINDINGS

Construct	Key Findings
Personality	The constructs of personality positively impact the intellectual performance of students. It helps in making students organized, bring dutifulness, open them to accept new challenges and difficulties and try to solve those with new methods and technologies. Students should avoid delaying the work and interact with their peers in a limited manner. They should strengthen their cognitive skills and should have moderate neuroticism.
Motivation	It has been found that students with a high locus of control, intrinsically motivated, having positive thoughts and attitude, focus towards their goals, not get distracted easily and self-efficient tend to score high marks as compared to their counterparts. Also, students seeking external motivation are less likely to obtain academic success.
Self-regulation strategies for learning	Students should rehearse for the topics covered in the classrooms, interact with their class fellows and friends to solve the problems, have good reasoning skills and mental abilities to enhance their learning. Besides they should put their best efforts to understand and solve the problems.
Psychosocial contextual influences	Social and academic integration make students feel at home and help them in learning from their peers and instructors easily. This benefit in the case if the student is not able to attend the class due to some urgency. It further reduces the stress levels in students by giving them a friendly environment.
Approach towards learning	Students should learn the background details and deep concepts about the subject matter to fully understand the topic. This makes learning effective and students will then be able to practically implement the learning.
Demographic	It has been noticed that students belonging to middle or upper socioeconomic status usually score high marks.

The research has various implications. Firstly, it has been found students should stay in an organized manner and oblige to the rules stated by their mentors. They should actively participate in the classroom discussions and should be extrovert in a limited manner to solve their subject related problems as communicating with peers can help gain knowledge outside the domain too. Extraversion also consists of sociability and is one of the prominent parameters in personality traits [40]. Extroverts are more determined and impulsive, less stressed, and less thoughtful and self-preoccupied than their counterparts [78]. Also, extrovert students have leadership qualities and have more friends [78]. Hence extraversion makes students ambitious, enthusiastic and affable. In line with Judge, Higgins, Thoresen and Barrick [40] and Watson and Clark [78] it is found that in current study extraversion has a moderate positive effect on Indian students. They should avoid last-minute submissions and complete their tasks timely. Students who worry much about their marks may feel depressed and hence not able to score high as stress deviate their mind and they lose focus. Also, students should have cognitive skills; try innovative ways to solve a problem and moderate agreeableness to enhance learning.

Secondly, Student's own interest in the course, will to study and aim to achieve their goals score high marks in contrast to those who seek extrinsic motivation. They should put their best efforts into completing the assigned projects or assignments and should expect a positive outcome of it. They should be optimistic about their future and be regular in classroom lectures. Students should focus on their goals and have faith and confidence in their academic efficiencies. They should work hard and concentrate well to achieve them.

Third, Career selection is at utmost priority for most students and so they should be a concern and moderately anxious about it. Practicing things will help students in commemorating the contents and to explain and write well in exams. Studying in detail the contents covered in the classroom and analyzing it helps students to build their cognitive abilities. Also, involved in activities enforcing peer discussions facilitate learning. Learning from peer discussions and managing time to study will help students improve their academic capability. Students should also prepare early for their exams and focus on their academics.

Forth, learning strategies referring to activities directly linked to the intellectual learning of students need to be analyzed properly to achieve high marks. Students who are anxious about their academic scores are more responsible and focused on their future. Students should have in-depth knowledge of the concepts. This will help in developing their analytical skills and in scoring high marks.

Fifth, social integration referring to the way students adapt to the social life of the university helps in building a friendly environment for students. Academic integration describing the way students adapt to the academic way of life help in learning with peers and class fellows and teachers easy. It helps students in solving complex problems easily and reduces stress and depression in students.

Sixth, although it has been found that demographic feature does not fully contribute to the intellectual performance of students. Students' belonging to upper or middle socioeconomic status score high marks and avail more learning facilities than those belonging to lower socioeconomic status.

Seventh, the Indian education sector is getting weak. To test the education level of the young generation in India, a survey is done and according to the report by Aser Center, it has been found that 40% of youth are not able to read a simple sentence in English and do the basic calculation. This results in low academic performance and decreases job rate. Youth are the future of the country and this makes it a major societal problem. This problem can be eliminated by enhancing the academic performance of students and provides benefits to the education sector. Education system is revived from time to time to take care of the dynamic needs of industry and the model is bridging the gap between education and industry need. This further increase employability as the industry and education sector is linked.

Based on the results obtained from the analysis, recommendations can be generated for the students to improve their learning behaviour and to score high in academics.

6. Limitations And Future Scope

The study significantly contributes from the theoretical and empirical point of view; however, there are certain other elements need to be integrated to extract maximal benefits from it.

At first, the study is confined to the students of metropolitan and urban cities and it does not include data of rural students and remote areas. The data includes students of distinct colleges; however, the probability that a student belongs to non-metropolitan city is rare. The study hence can be expanded to include students nationwide. The study considers diverse population and hence the model can be applied to any educational institute involving diversified populace.

Secondly, the present study has covered psychometric behaviour and patterns as depicted by the students. Besides some other key parameters like genetic impact, environmental effects on the learning and upbringing of the student, parent education, type of learning skills, etc. can be considered to enhance the outcome of this study. These parameters might impact learners' understanding.

The impact of constructs on their actual performance and the deviations that exist from actual to expected results are yet to be analyzed. The study can be expanded to include all the parameters as stated above to strengthen the outcome of the research. Also, it can be extended to include the students across the nation and the model can be tested using different statistical and machine learning techniques.

REFERENCES

[1] P. L. Ackerman and E. D. Heggestad, "Intelligence, personality, and interests: Evidence for overlapping traits.," Psychol. Bull., vol. 121, no. 2, pp. 219–245, 1997, doi: 10.1037//0033-2909.121.2.219.

[2] S. Aksoy and R. M. Haralick, "Feature normalization and likelihood-based similarity measures for image retrieval," Pattern Recognit. Lett., vol. 22, no. 5, pp. 563–582, 2001, doi: 10.1016/S0167-8655(00)00112-4.

[3] J. Anderson Koenig, Assessing 21st century skills: Summary of a workshop, Washington DC: The National Academic Press, 2011, http://dx.doi.org/10.17226/13215

[4] R. W. Baker and B. Siryk, SACQ student adaptation to college questionnaire, 2nd ed., Los Angeles: Western Psychological Services, 1999.

[5] A. Bandura, Self-efficacy: The exercise of control, New York, NY: Freeman, 1997.

[6] R. M. Bell, Y. Koren and C. Volinsky, The bellkor solution to the netflix prize. KorBell Team's Report to Netflix, 2007.

[7] J. Biggs, D. Kember and D. Y. Leung, "The revised two-factor study process questionnaire: R-SPQ-2F", British journal of educational psychology, vol. 71, no. 1, pp. 133-149, 2001.

[8] A. Binet and T. Simon, "The development of intelligence in children:(the Binet-Simon scale)", vol. 11, Williams & Wilkin, 1916.

[9] L. S. Blackwell, K. H. Trzesniewski and C. S. Dweck, "Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention", Child Development, vol. 78, no. 1, pp. 246‐263, 2007.

[10] S. Bochner, B. M. McLeod and A. Lin, "Friendship patterns of overseas students: A functional model," International Journal of Psychology, vol. 12, no. 4, pp. 277–294, 1977.

[11] M. Boekaerts and L. Corno, "Self-regulation in the classroom: A perspective on assessment and intervention," Applied Psychology, vol. 54, pp. 199–231, 2005, doi:10.1111/j.1464-0597.2005.00205.x.

[12] L. A. Bressler, M. E. Bressler and M. S. Bressler, "The role and relationship of hope, optimism and goal setting in achieving academic success: A study of students enrolled in online accounting courses," Academy of Educational Leadership Journal, vol. 14, no. 4, pp. 37, 2010.

[13] M. W. Browne, R. Cudeck, K. A. Bollen and J. S. Long, Testing structural equation models, 1993.

[14] D. L. Butler, B. Beckingham and H. J. N. Lauscher, "Promoting strategic learning by eighth-grade students struggling in mathematics: A report of three case studies," Learning Disabilities Research and Practice, vol. 20, no. 3, pp. 156‐174, 2005.

[15] J. P. Byrnes, "Factors predictive of mathematics achievement in White, Black, and Hispanic 12th graders," Journal of Educational Psychology, vol. 95, 2003, pp. 316‐326.

[16] P. A. Carpenter, M. A. Just and P. Shell, "What one intelligence test measures: A theoretical account of the processing in the Raven Progressive Matrices Test", Psychological Review, vol. 97, 1990, pp. 404–431, doi:10.1037/0033-295X.97.3.404.

[17] S. Cassidy*, "Learning styles: An overview of theories, models, and measures", Educational psychology, vol. 24, no. 4, pp. 419-444, 2004.

[18] H. Cen, K. Koedinger and B. Junker, "Learning factors analysis–a general method for cognitive model evaluation and improvement", International Conference on Intelligent Tutoring Systems, pp. 164-175, 2006, Springer, Berlin, Heidelberg.

[19] T. Chamorro-Premuzic and A. Furnham, "Personality, intelligence and approaches to learning as predictors of academic examination performance", Personality and Individual Differences, vol. 44, pp. 1596–1603, 2008, doi: 10.1016/j.paid.2008.01.003.

[20] G. A. Churchill Jr, "A paradigm for developing better measures of marketing constructs", Journal of marketing research, vol. 16, no. 1, pp. 64-73, 1979.

[21] T. J. Cleary, A. Gubi and M. V. Prescott, "Motivation and self-regulation assessments in urban and suburban schools: Professional practices and needs of school psychologists", Psychology in the Schools, vol. 47, no. 10, pp. 985‐1002, 2010.

[22] P. T. Costa, Jr. and R. R. McCrae, R. R., NEO-PI–R professional manual. Odessa, FL: Psychological Assessment Resources, 1992.

[23] F. I. M. Craik and R. S. Lockhart, "Levels of processing: A framework for memory research", Journal of Verbal Learning and Verbal Behaviour, vol. 11, pp. 671–684, 1972 doi:10.1016/S0022-5371(72)80001-X.

[24] E. L. Deci and A. C. Moller, A. C., The Concept of Competence: A Starting Place for Understanding Intrinsic Motivation and Self-Determined Extrinsic Motivation, 2005.

[25] G. W. Dekker, M. Pechenizkiy and J. M. Vleeshouwers, "Predicting Students Drop Out: A Case Study", International Working Group on Educational Data Mining, 2009.

[26] J. M. Dennis, J. S. Phinney and L. I. Chuateco, "The role of motivation, parental support, and peer support in the academic success of ethnic minority first-generation college students", Journal of College Student Development, vol. 46, pp. 223–236, 2005, doi:10.1353/csd.2005.0023.

[27] C. Dignath and G. Büettner, "Components of fostering self-regulated learning among students. A meta-analysis on intervention studies at primary and secondary school level", Metacognition and Learning, vol. 3, 2008, pp. 231‐264.

[28] A. Diseth and Ø. Martinsen, "Approaches to learning, cognitive style, and motives as predictors of academic achievement", Educational psychology, vol. 23, no. 2, pp. 195-207, 2003.

[29] T. G. Duncan and W. J. McKeachie, "The making of the Motivated Strategies for Learning Questionnaire", Educational Psychologist, vol. 40, 2005, pp. 117–128. doi:10.1207/s15326985ep4002_6.

[30] J. S. Eccles and A. Wigfield, "Motivational beliefs, values, and goals", Annual Review of Psychology, vol. 53, pp. 109 –132, 2002, doi:10.1146/ annurev.psych.53.100901.135153.

[31] A. Elbadrawy, A. Polyzou, Z. Ren, M. Sweeney, G. Karypis and H. Rangwala, "Predicting student performance using personalized analytics", Computer, vol. 49, no. 4, pp. 61-69, 2016.

[32] S. A. Elkins, J. M. Braxton and G. W. James, "Tinto's separation stage and its influence on first-semester college student persistence", Research in Higher Education, vol. 41, pp. 251–268, 2000, doi:10.1023/A: 1007099306216.

[33] N. Entwistle, H. Tait and V. McCune, "Patterns of response to an Approaches to Studying Inventory across contrasting groups and contexts", European Journal of Psychology of Education, vol. 15, pp. 33–48, 2000.

[34] N. Entwistle, "Styles of learning and approaches to studying in higher education," Kybernetes, vol. 30, no. 5/6, pp. 593-603, 2001.

[35] M. Feng, N. Heffernan and K. Koedinger, "Addressing the assessment challenge with an online system that tutors as it assesses", User Modeling and User-Adapted Interaction, vol. 19, no. 3, pp. 243-266, 2009.

[36] K. I. Ghauth and N. A. Abdullah, "Learning materials recommendation using good learners' ratings and content-based filtering", Educational technology research and development, vol. 58, no. 6, pp. 711-727, 2010.

[37] H. Hamsa, S. Indiradevi and J. J. Kizhakkethottam, "Student academic performance prediction model using decision tree and fuzzy genetic algorithm", Procedia Technology, vol. 25, pp. 326-332, 2016.

[38] J. Heckhausen, C. Wrosch and R. Schulz, "A motivational theory of life-span development", Psychological review, vol. 117, no. 1, pp. 32, 2010.

[39] C. T. Huang, W. T. Lin, S. T. Wang and W. S. Wang, "Planning of educational training courses by data mining: Using China Motor Corporation as an example", Expert systems with applications, vol. 36, no. 3, pp. 7199-7209, 2009.

[40] T. A. Judge, C. A. Higgins, C. J. Thoresen and M. R. Barrick, "The big five personality traits, general mental ability, and career success across the life span", Personnel psychology, vol. 52, no. 3, 1999, pp. 621-652.

[41] M. Kornhaber, Howard Gardner, In The Development and Education of the Mind, pp. 18-22, 2006, Routledge.

[42] P. H. Kvam, "The effect of active learning methods on student retention in engineering statistics" The American Statistician, vol. 54, no. 2, pp. 136-140, 2000.

[43] H. M. Lefcourt, Locus of control, Academic Press, 1991.

[44] R. I. Levin and D. S. Rubin, Statistics for Management, Prentice Hall, 6th Edition, the University of California 1018 pages, ISBN: 9780138477813, 1998.

[45] J. Mandel, "Use of the singular value decomposition in regression analysis", The American Statistician, vol. 36, no. 1, pp. 15-24, 1982.

[46] M. Mannan, "Student attrition and academic and social integration: Application of Tinto's model at the University of Papua New Guinea", Higher Education, vol. 53, no. 2, 2007, pp. 147–165.

[47] N. Manouselis, H. Drachsler, R. Vuorikari, H. Hummel and R. Koper, "Recommender systems in technology enhanced learning", Recommender systems handbook, pp. 387-415, 2011, Springer, Boston, MA.

[48] N. Milgram, G. Mey-Tal and Y. Levison, "Procrastination, generalized or specific, in college students and their parents", Personality and Individual Differences, vol. 25, pp. 297–316, 1998, doi:10.1016/S0191-8869(98)00044-0.

[49] M. K. Mount and M. R. Barrick, Manual for the Personal Characteristics Inventory, Libertyville, IL: Wonderlic, 1995.

[50] S. E. Newstead, "A study of two "quick-and-easy" methods of assessing individual differences in student learning", British Journal of Educational Psychology, vol. 62, pp. 299–312, 1992.

[51] M. P. O'Mahony and B. Smyth, A recommender system for on-line course enrolment: an initial study, 2007.

[52] R. Pekrun, T. Goetz, W. Titz and R. P. Perry, "Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research", Educational psychologist, vol. 37, no. 2, pp. 91-105, 2002.

[53] R. Pekrun, T. Goetz, R. P. Perry, K. Kramer, M. Hochstadt and S. Molfenter, "Beyond test anxiety: Development and validation of the Test Emotions Questionnaire (TEQ)", Anxiety, Stress & Coping,vol. 17, pp. 287–316, 2004, doi:10.1080/10615800412331303847.

[54] P. R. Pintrich, "A conceptual framework for assessing motivation and self-regulated learning in college students", Educational Psychology Review, vol. 16, pp. 385–407, 2004, doi:10.1007/s10648-004-0006-x.

[55] A. E. Poropat, "A meta-analysis of the five-factor model of personality and academic performance", Psychological Bulletin, vol. 135, 2009, pp. 322–338. doi:10.1037/a0014996.

[56] F. Preckel, H. Holling and M. Vock, "Academic underachievement: Relationship with cognitive motivation, achievement motivation, and conscientiousness", Psychology in the Schools, vol. 43, no. 3, pp. 401-411, 2006.

[57] J. R. Quinlan, Induction of Decision Trees. Machine Learning, 1, 1986.

[58] S. Rendle, C. Freudenthaler and L. Schmidt-Thieme, "Factorizing personalized markov chains for next-basket recommendation", Proceedings of the 19th international conference on World wide web, pp. 811-820, 2010 April, ACM.

[59] M. Richardson, C. Abraham and R. Bond, "Psychological correlates of university students' academic performance: A systematic review and meta-analysis", Psychological bulletin, vol. 138, no. 2, pp. 353, 2012.

[60] R. Riemann, A. Angleitner and J. Strelau, "Genetic and environmental influences on personality: A study of twins reared together using the self-and peer report NEO–FFI scales", Journal of Personality, vol. 65, pp. 449–475, 1997.

[61] S. B. Robbins, K. Lauver, H. Le, D. Davis, R. Langley and A. Carlstrom, "Do psychosocial and study skill factors predict college outcomes? A meta-analysis", Psychological Bulletin, vol. 130, pp. 261–288, 2004, doi: 10.1037/0033-2909.130.2.261.

[62] E. L. Rolfhus and P. L. Ackerman, "Assessing individual differences in knowledge: Knowledge structures and traits", Journal of Educational Psychology, vol. 91, pp. 511–526, 1999, doi:10.1037/0022-0663.91.3.511.

[63] C. Romero, S. Ventura, P. G. Espejo and C. Hervás, Data mining algorithms to classify students, Educational data mining, 2008.

[64] J. Russell, D. Rosenthal and G. Thomson, "The international student experience: Three styles of adaptation", Higher Education, vol. 60, no. 2, pp. 235–249, 2010.

[65] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being", American Psychologist, vol. 55, pp. 68–78, 2000, doi:10.1037/0003-066X.55.1.68.

[66] E. Sadler-Smith, "Learning style: frameworks and instruments:, Educational Psychology, vol. 17, pp. 51–63, 1997.

[67] S. Severiens and R. Wolff, "A comparison of ethnic minority and majority students: Social and academic integration, and quality of learning", Studies in Higher Education, vol. 33, pp. 253–266, 2008.

[68] J. Smith and R. Naylor, "Determinants of degree performance in UK universities: A statistical analysis of the 1993 student cohort", Oxford Bulletin of Economics and Statistics, vol. 63, pp. 29–60, 2001, doi:10.1111/1468- 0084.00208.

[69] P. Steel, "The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure", Psychological Bulletin, vol. 133, pp. 65–94, 2007, doi:10.1037/0033-2909.133.1.65.

[70] J. Stoecker, E. T. Pascarella and L. M. Wolfle, "Persistence in higher education: A 9-year test of a theoretical model", Journal of College Student Development, vol. 29, pp. 196–209, 1988.

[71] M. Sweeney, H. Rangwala, J. Lester and A. Johri, Next-term student performance prediction: A recommender systems approach, 2016, arXiv preprint arXiv:1604.01840.

[72] M. Tayefi, H. Esmaeili, M. S. Karimian, A. A. Zadeh, M. Ebrahimi, M. Safarian, M. Nematy, S. M. Reza Parizadeh, G. A. Ferns and M. Ghayour-Mobarhan, "The application of a decision tree to establish the parameters associated with hypertension", Computer methods and programs in biomedicine, vol. 139, pp. 83-91, 2017.

[73] N. Thai-Nghe, A. Busche and L. Schmidt-Thieme, "Improving academic performance prediction by dealing with class imbalance", Ninth International Conference on Intelligent Systems Design and Applications, pp. 878-883, 2009, IEEE.

[74] N. Thai-Nghe, L. Drumond, T. Horváth, A. Nanopoulos and L. Schmidt-Thieme, "Matrix and Tensor Factorization for Predicting Student Performance", CSEDU, (1), pp. 69-78, 2011.

[75] N. Thai-Nghe, P. Janecek and P. Haddawy, "A comparative analysis of techniques for predicting academic performance", 37th annual frontiers in education conference-global engineering: knowledge without borders, opportunities without passports, pp. T2G-7, 2007, IEEE.

[76] V. Tinto, "Colleges as communities: Taking research on student persistence seriously", The Review of Higher Education, vol. 21, no. 2, pp. 167–177, 1998.

[77] Y. J. Vermetten, H. G. Lodewijks and J. D. Vermunt, "The role of personality traits and goal orientations in strategy use", Contemporary Educational Psychology, vol. 26, pp. 149–170, 2001, doi:10.1006/ceps.1999.1042.

[78] D. Watson and LA. Clark, Extraversion and its positive emotional core, In Hogan R, Johnson J, Briggs S Eds., Handbook of personality psychology, pp. 767-793, San Diego, CA. Academic Press, 1997.

[79] B. Weiner, An attributional theory of motivation and emotion, New York, NY: Springer-Verlag, 1986.

[80] P. Wilcox, S. Winn and M. Fyvie-Gauld, "It was nothing to do with the university, it was just the people: The role of social support in the first-year experience of higher education", Studies in Higher Education, vol. 30, no. 6, pp. 707–722, 2005.

[81] Ian H. Wittenand E. Frank," Data Mining: Practical machine learning tools and techniques", 2nd ed., Morgan Kaufmann, USA, ISBN: 0-12-088407-0, Association Rule Mining of Distributed Level Hierarchy in Web, International Journal of Advanced Research in Computer Science, vol. 2, pp. 311-314, 2005.

[82] C. Wolters, P. Pintrich and S. Karabenick, "Assessing academic self-regulated learning", Indicators of Positive Development Conference, Child Trends, Washington, DC, 2003.

[83] M. Zeidner and G. Matthews, Intelligence and personality, R. Sternberg (Ed.), Handbook of intelligence, 2nd ed., pp. 581–610, 2000, New York, NY: Cambridge University Press.

[84] N. Zepke and L. Leach, "Integration and adaptation", Active Learning in Higher Education, vol. 6, no. 1, pp. 46–59, 2005.

[85] Y. Zhou, D. Jindal-Snape, K. Topping and J. Todman, "Theoretical models of culture shock and adaptation in international students in higher education", Studies in Higher Education, vol. 33, no. 1, pp. 63–75, 2008.

[86] B. J. Zimmerman, "Becoming a self-regulated learner: An overview", Theory into practice, vol. 41, no. 2, pp. 64-70, 2002.

Dr. Iti Burman obtained her Master degree in Computer Applications from Guru Gobind Singh Indraprastha University, India. She is PhD in Information Technology from internationally reputed Amity University, Noida, UP. She is currently working as Assistant Professor in IT Department at Vivekananda Institute of Professional Studies, Delhi, India. She has experience of more than 9 years in both industry and academia. She holds first position in Graduation, third position in Post-Graduation and awarded with Bronze medal for excellence in academics. She has published various research papers in reputed international/national journals and conferences. Her research articles have been cited in more than 28 research papers. She has received best paper award for one of her research papers in the year 2018 in an international conference. She acted as Reviewer and TPC member in various international conferences. Her fields of interest include Data Analytics, Data Mining, Internet of Things, Networking, Block Chain etc.

Prof. (Dr.) Subhranil Som received his PhD in Computer Science and Engineering from University of Kalyani, West Bengal. He is currently Principal of Bhairab Ganguly College, Kolkata, West Bengal. He holds a Distinction in Physics and Mathematics in Graduation from Jadavpur University, Kolkata, India. His fields of interest include Cryptography, Network Security, Information Security, e-Health, Robotics, IoT, Core Java, other programming languages etc. He has 4 PhD awarded under his supervision and 1 submitted for the same. He has filed 12 Patents out of which 7 published in Official Journal of the Patent Office, India. He has published more than 110 research papers in reputed International, National journals and conferences and author of 2 books and 1 upcoming book. He has done the Certification in CISCO (IT Essential 5.0), CISCO (CCNAv7: Introduction to Network), Cyber Security and Deep Learning, Best Practices in Higher Education Institution. He was attached with a WHO's International Research Project on "e-Health for Health Care Delivery", University of New South Wales, Sydney, Australia. He has visited to Australia, Singapore, Thailand and UAE for his academic and research work. He is a member of several professional bodies such as Senior Member of IEEE, IAENG, IACSIT, ISOC, Life Time Member of AUN Research Lab. He has organized several International conferences in India and Abroad. He acted as Conference Chair, Session Chair, Reviewer, TPC member of different International Journals and Conferences. He has more than 17 years of teaching and research experiences.

Prof. (Dr.) Syed Akhter Hossain is currently working as Professor and Head of the Department of Computer Science and Engineering at Daffodil International University since 2010. Professor Hossain obtained B.Sc. and M.Sc. in Applied Physics and Electronics with Gold medal and distinction and Ph.D. in Computer Science and Engineering from University of Dhaka. As Erasmus Mundus post-doctoral fellow, he contributed in the area of Informatics and Industrial Engineering with University Lumiere Lyon 2 in France. He has more than 30 years of working experience in industry, education, research and training. He is actively involved in research guidance/ research projects/ research collaborations with Institutes/ Industries and has more than 160 publications/ presentations and his work been listed in DBLP, IEEE Explore and other research databases. He works closely with the ICT Division of the Ministry of Post, Telecommunication and IT of the Government of the Peoples Republic of Bangladesh. He received several national and international awards for his outstanding contribution in ICT education, innovative projects for the visually impaired people. He also received other International awards for his scholastic works specially for the contribution of machine translator for Bangla Braille used by the visually impaired society. His current research interests include Machine Learning and AI with Natural Language Processing.