Personality Trait-Aware Educational Suggestion Platform

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ABSTRACT
In the sectors of e-commerce, social networks, and news recommendation, personalized recommendation systems have recently emerged as a crucial technology. However, the advancement of a personalized recommendation system in the sphere of education and instruction is very gradual and lacks a corresponding application. The caliber of students' thinking is crucial to learning and may affect how well they perform. Different students process, encode, recall, analyze, and put in their acquired knowledge in multiple ways, some are thoughtful learners, while others are quick learners. Personality is linked to these individual variations in favored learning strategies and information processing speed. Where both personality factors and learning preferences are expected to have a significant impact on especially e-learners' academic performance. The largest problem that currents e-learning management systems confront is giving users access to high-quality content linked to their interests and minimizing the time that users must spend searching for this content. In addition, not all students can follow the same learning path to comprehend a single piece of text due to differences in reading abilities and differences in personality types.

The diversity of content that is offered to students on the internet may overwhelm some of them because it doesn't necessarily correspond to their reading habits. This is crucial because, according to a psychologist, kids should be taught in accordance with their preferred reading manner. Therefore, based on the user's personality and learning style, e-learning strategies can be recommended to them. In this project, the Big Five Personality Traits are used to identify personalities and Index of Learning Style to determine the student's preferred learning style in order to create a personality-aware recommendation system.

Keywords
Big Five, Recommendation system, (IPIP) International Personality Item Pool, Index of Learning Style, Personality aware recommendation system.

1. INTRODUCTION
Like other educational environments, the e-learning environment has created a unique psychological space. It is well acknowledged in the associated literature that both learning style and personality qualities have a significant impact on students, and both factors have been extensively researched (Conard, 2006).

To explore and analyze the academic behavior of students, personality type & learning styles are the two fundamental factors that have been identified as trusted sources from the standpoint of e-learning. (Hamburger & Ben-Artzi, 2003). In above and following papers its concluded that, there is a valid and indisputable connection between personality traits, learning preferences, and academic achievement [13]. It is incredibly challenging to switch learning materials between students and faculty due to the development of technology, the continuous rise in student capacity, and the number of departments in educational institutions.

Personality model: There is no overarching theory that provides a thorough explanation of human personality. While some theories link personality differences to socioeconomic influences, others attribute them to heredity. Numerous personality models, including the Big Five personality traits model, MBTI, Eysenck personality model, and HEXACO personality model, have undergone in-depth psychological study. These personality models differ in how they depict human personality; some (such as the MBTI) believe that people have different "personality types," while others depict personality as a spectrum of personality qualities (Big-Five, Eysenck and HEXACO).

From the standpoint of personality computing, the Big-Five model and other theories of personality traits have been used in the majority of earlier publications.

Big five model: The Big Five, also called the OCEAN of personality traits, developed by Costa and McCrae, has become an all-known and trusted model for examining and analyzing the relationship between personality and various spans of academic performance. The "Big Five" personality qualities are thought to represent the five core facets of personality by many modern personality psychologists. Extraversion (sometimes known as extroversion), agreeableness, openness, conscientiousness, and neuroticism are the five main personality qualities. People with varying levels of neuroticism are assessed, from sensitive and 6 anxious to secure and confident. The field of agreeability assesses persons on a spectrum from amiable and compassionate to analytical and detached. The field of conscientiousness assesses individuals ranging from productive and well organized to loose-lipped and reckless. The field of openness to experience assesses individuals ranging from creative and inquisitive to reliable and cautious. The extraversion field assesses individuals ranging from gregarious and active to isolated and reserved. The results are then graded on a scale of 1 to 5. According to earlier studies, people working in fields like career development are becoming more interested in personality prediction.

Learning styles and personality: There are fascinating connections between personality qualities and learning preferences, according to research. For instance, it has been demonstrated that students who absorb information deeply are more likely to use appropriate study techniques, draw valid conclusions, and exhibit self-regulation than students who prefer to process information superficially (Gadzella, Ginther, Masten, & Gutrie, 1997). Deep-processing pupils are more likely to be diligent, academically interested, and extraverted, according to Furnham (1992) and Zhang (2003). Such students are also emotionally stable, according to Geisler-Brenstein, Schmeck, and Hetherington (1996). According to Zhang (2003), a student may be more prone to anxiety and worry if they prefer intuitive processing and a structured learning environment.

Personality aware recommendation: The most popular model in psychology and personality computing is the Big-Five model of personality traits, sometimes known as the five-factor model (FFM). According to the Big Five paradigm, the five elements are, in order of importance: neuroticism, conscientiousness, extraversion, agreeableness, and openness to experience. And frequently, the letters OCEAN or CANOE stand in for these characteristics. The system then moves on to the personality similarity measurement, where it attempts to link the newly discovered personalities. The neighbours who share the most personality traits with the joined user. The cold-start problem is fixed by this process, which enables the personality-aware recommendation system to make recommendations purely based on personality data. After completing the cold-start process and beginning to rate, the user rating is used into the recommendation system's overall similarity measurement to refine the group of neighbours.

2. LITERATURE SURVEY

Rajib Ahmed Faisal proposed that the two main things to be taken under consideration in the education field are: learning methods and personality types [1]. Personality types and learning styles of high school students have been focused. Those students learn English as a foreign language. Also looks at whether there are any notable variations in the personality types and learning methods of students from different locations and considers other demographic factors bothering the studies. The personality inventory used was Big Five Inventory (BFI) and the learning style used was VARK inventory. As a result, a descriptive analysis of personality types, learning methods and academic attainment of the surveyed students was given.

Enjy Abouzeid, used Big Five Inventory (BFI) and VARK inventory as the personality and learning style inventory respectively [2]. At a medical University in Egypt, a survey was made. The survey involved 333 first-year medical students belonging to UG degrees. According to study results, the preferred learning technique among pupils is the kinesthetic technique. When it comes to learning techniques, both boys and girls show notable variations. Also, auditory learning links kinesthetic techniques and accomplishments in academics.

Nabia Luqman Siddiquei & Ruhi Khalid, 150 students enrolled in various degree programs received a booklet containing a population tally, the Big Five Inventory (BFI), and the Index of Learning Style (ILS) [3]. It takes about 10 to 25 minutes to finish the questionnaire. The Total responses were about 140 in number. As a result, a descriptive analysis of personality types, learning methods, and academic attainment of the surveyed students was given. When it comes to 9 learning techniques, both boys and girls show notable variations.

Lindsey Childs-Kean & Mary Edwards proposed that using learning techniques foundations in health & science education gives more concentration to learning styles to increase self-awareness [4]. In this review, it was discovered that health science education makes use of a variety of learning style theories. Most of the articles found were illustrative studies, and others had minimal dependence on academic results. Future research should aim to provide answers to these issues because there is not much-published data on how to use learning techniques foundations in health & science education effectively and little information on how to use them to increase student self-awareness.

J. Dhilipan et al, presented comparison research on supervised learning for student prediction. 14 features are used by the author to classify [5]. KNN, Decision trees, and Naive Bayes are the classification tools employed. By utilizing the student's intellectual characteristics that have an impact on their academic performance, a neurometrics study of student behavior has been presented. Use different mining approaches. By applying the suggested system, the accuracy rate has been raised from 89% in the prior study to 90%. To get greater precision in this case, the author used a Radial Basis Function Kernel.

Abdallah Namoun & Abdullah Alshanqiti presented a survey which is one of the earliest attempts to integrate the sophisticated paradigms and models used in education to forecast the achievement of student learning outcomes, which serve as a stand-in for student performance [6]. The survey highlights a number of significant issues and offers suggestions for further study in the area of educational data mining. It used the eight specified guidelines to judge the quality of the combined studies. These recommendations were created to assess the data analytics models

Lubna Mahmoud Abu Zohair, proposed that predicting student performance has become a pressing need in the majority of educational institutions [7]. That is necessary to support at-risk students, ensure their retention, provide top-notch learning materials, and raise the university's standing and reputation. Dataset was prepared to be passed through visualization and clustering techniques in order to extract the top correlated indicators. Feature selection, normalization, attribute selection phase, and classification model evaluation is carried out. Among a lot of Machine Learning algorithms, MLP-ANN was used here.

Gafarov F.M & Rudneva Ya.B, proposed a study to identify the factors that influence students' academic progress and to examine those factors using machine learning and artificial neural networks[8]. The data was processed and analyzed using Python programming, SPSS Statistics, and data mining techniques. Data on student performance at Kazan Federal University from 2012 to 2019 were examined for the study.

Initial findings indicated that information analytical systems that can model or visualize data as well as predict steady trends have a high potential for success. The growth of this field of academic (educational) analytics will aid in the creation of tailored interventions for various student groups in accordance with their potential.

Dongxuan Wang & Dapeng Lian proposed a system used to develop performance prediction systems and study the variation in academic performance among Chinese undergraduates [9]. A questionnaire was created to gather information in accordance with the findings of prior studies and the current circumstances of Chinese college students. Second, the questionnaire's contents were examined, and its key characteristics were determined using the chi-square test. Third, four categorization prediction models are created by machine learning using the key attributes as input. The experiment demonstrates that stable effect is provided by the support vector machine classifier (SVC) models.

Izzak Dekker & Elisabeth M says that one in three students withdraw from college without earning the degree for which they entered. According to research, students who struggle to acclimatize to tertiary education may have mental health issues as well as academic underperformance [10]. The advantage of being scalable and consequently less expensive is one advantage of internet-based or digital forms of mental health care. A chatbot is being built that plays a catalytic role like an intervention that supports users in engaging themselves.

Miguel A. Sahagun & Randy Moser, developed and tested the growth mindset method, In order to help undergraduate students establish a growth mindset belief system about their own potential [11]. Pupils may have a fixed mindset and think that their personal characteristics are unchangeable, or they may have a growth mindset and think that, with work, they can cultivate, grow, and improve their characteristics. A pretest-posttest control group design was employed to validate a growth mindset instructional strategy based on psychology. In two different courses, this growth-mindset teaching technique was employed in 17 sections in total. As a control group, 14 extra sections were taught using the lecture method. When compared to lecturing, students exposed to the growth-mindset teaching approach had better growth mindset beliefs and had less fixed-mindset beliefs.

Andrew J Cavanagh, Xinnian Chen, analyzes student dedication to and involvement in active learning are both correlated with student trust in the instructor and student’s perceptions of their intelligence [12]. Student trust in the teacher was a significant factor in achieving targeted student outcomes in an active-learning setting where students are more actively involved in the learning process. using control groups when teaching. When compared to lecturing, students exposed to the growth-mindset teaching approach had better growth mindset beliefs and had less fixed-mindset beliefs.

Meera Komarraju, Steven J. Karau, Ronald R. Schmeck, Alen Avdic, summarized that, there is a valid and indisputable connection between personality traits, learning preferences, and academic achievement [13]. It has been shown through it how personality factors and learning styles have affected academic attainment. It follows that these criteria are pertinent to one another. According to the combination of both personality traits and learning styles, the outcome of academic accomplishment may be influenced by both personality traits and learning styles.

Lalita Na Nongkhai, Thongchai Kaewkiriya has proposed an approach on designing a framework for e-Learning Recommendation based on Index of Learning Style Model with data mining using WEKA Tool [14]. They did a student survey by questionnaire from the learners of Thai-Nichi of Technology (N=600). The analysis was done by gathering all the details from the student survey. The details collected were from 44 questions of ILS Testing Inventory, student general details and 6 fixed necessary questions. This framework can approximately forecast the suitable and best learning style for Learners/Students by employing WEKA Algorithm with J48 to classify and predict learning styles for each learner. Decision Tree algorithm was used to classify with accuracy of 76.92% , Decision Tree LMT and Naïve Bayes were other two algorithms taken for comparison the expert's evaluation the framework received an average satisfaction level of 3.87.

Shaimaa M. Nafea, Francois Siewe and Ying He, addresses the challenge of improving the quality of e-learning recommendation systems for delivering personalized course learning objects based on the student's preference [15]. So they have proposed a novel recommender algorithm for machine learning which combines student actual rating of the course with their learning style to recommend personalized course learning objects (LOs). Here they have the both learning styles of the students and the profiles of the learning objects represented by the Felder Silverman Learning Styles Model (FSLSM).The experiment's findings demonstrate that the hybrid recommendation algorithm they have proposed is the best technique for making recommendations. Using FSLSM representations of student learning styles and learning object profiles, it addresses the challenges of cold-start and rating sparsity. To increase prediction accuracy, it also incorporates collaborative filtering and content-based filtering techniques.80 students were used as test subjects for this approach.

Yaman Köseoğlu discovers the intriguing relationships between the Big Five personality traits, learning preferences, and academic success and suggests that personality characteristics and learning preferences are key factors in determining academic success. [16]. For the research, 202 university students participated. They self-reported their grade point averages and completed the Assessment of Learning Processes Scale and Big Five personality traits questionnaires. According to the research findings, learning style contributed 5% to academic achievement and the Big Five personality traits accounted for 17% of the variance in grade point average.

Maleika Heenaye, Baby Ashwin Gobin, Naushad Ali Mamode Khan deduces learning styles of students from faculty of management and faculty of engineering through Felder-Solomon index of learning (ILS) questionnaire and analysis of the result obtained [17]. It concludes that learners from both faculties have different learning preferences. They argue that by acknowledging these disparities, it will be easier to accommodate the various learning requirements of both groups of pupils. Students studying computer science favour visual, sensory, and sequential in varying degrees.

Norasyikin Omar, Mimi Mohaffyza Mohamad, Aini Nazura Paimin proposes that in both technical and non-technical subjects, the purpose of this study was to ascertain the association between student achievement and learning style [18]. This survey included 288 Diploma students who were enrolled in the Electrical Engineering programme. Participants received the Solomon Felder Learning Style Index, and the results were analysed using the Felder and Silverman model. According to the results, electrical engineering students learn best in active ways for the first dimension, sensing for the second, visual for the third, and sequence for the fourth. The analysis findings indicated that for the topic of Electrical In conclusion, while learning style is not the primary element that increases students' achievement, it can be used to determine which learning types of students are likely to have.

Diana Zagulova, Viktorija Boltunova, Sabina Katalnikova, Natalya Prokofyeva4, Kateryna Synytsya addresses the issue of the growing demands for student's quality education and difficulties relating to a student's individualised learning process [19]. In this paper's objectives are to look into the relationship between learning style with academic success and to formulate suggestions for customized online learning that take each student's specific learning style into account. To identify the student's learning style, they have incorporated the Felder–Silverman model ILSQ (Index of Learning Style Questionnaire). It was analyzed and concluded that there were more sensing students than intuitive students, more visual students than verbal students, more sequential students than global students, and more activist students than reflector students. Yet, there was no discernible difference in the number of pupils on the Sequential/Global dimension.

Sahraoui Dhelim, Liming Luke Chen, Nyothiri Aung, Wenyin Zhang and Huansheng Ning proposes a unique personality model for personality aware recommendation systems which is a hybrid personality model for suggestion that benefits from both the concepts of personality traits and types [20].They suggested an alternative approach that addresses the issues of data sparsity and cold start that are faced by current recommendation systems. Therefore, the proposed hybrid personality model involving recommendation system was studied and contrasted with all the top suggested personality characteristic models and types of models. Three major personality models—the Big Five, the Eysenck, and the HEXACO—as well as one personality type were examined across four systems (MPTI). The effectiveness of their work was evaluated in terms of precision, recall, and F-Measure. The study came to the conclusion that the recommended hybrid model uses the personality type model to address the cold start issue and also incorporates the benefits of the personality traits model, making it well-suited for personality-aware recommendation systems.

3. PROPOSED SOLUTION

The proposed idea is to collect data from students in the form of questionnaire through a web interface .To identify their personality trait and learning style, two separate questionnaire is used.This recommendation system uses personality trait as context information, to help in the learning process of students.Through the integration of the personality trait and the learning style identified , the recommendation system gives suggestion to the particular student so as to improve their academic performance. The suggestion might include learning strategies and corresponding e-learning platforms as well.

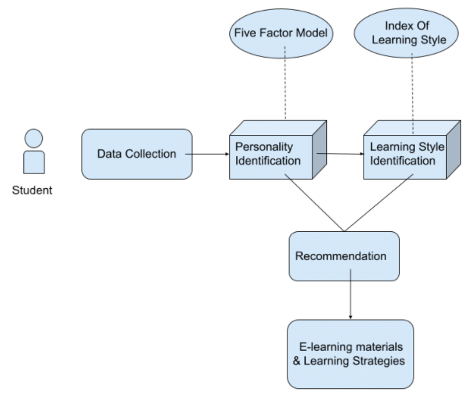

Figure 1:Workflow

Data Collection: To collect data from students , use a questionnaire that consists of two sets of questionnaire which includes personality trait inventory and learning style inventory. Data is collected through a web interface that will be circulated among the students to fill the two sets of questionnaires. The collected data will be used as a test data to check the working of the model. For personality identification, Big Five Personality trait Inventory is being used, which consists of 50 questions whose response scale was labeled between 1 to 5 from strongly agree to strongly disagree. For learning style identification, Index of Learning Style Inventory(Felder-Silverman) is used, which is a 44-item questionnaire whose response will lie between 2 options only. The Felder-Silverman learning styles model has four dimensions to evaluate preferences on each one.

Personality Identification : To identify the personality trait of a particular student, among multiple psychology theories available, Big Five Inventory is used. In this model, personality traits are being represented under the umbrella of the Five Factor model. It was the most widely accepted framework. This model has been used in numerous cultures and languages, which has led to research that not only confirms its validity as a theory of personality but also establishes the universality of its validity. So, rather than being based on neuropsychological research, this idea is focused on the associations between words. Dataset containing 1,015,342 questionnaire answers collected online by Open Psychometrics is used for training the machine learning model. After analysing the dataset, unsupervised learning algorithm K-Means Clustering is used for clustering the students into the respective personality clusters describing the 5 personality traits:

1. Openness to experience (inventive/curious vs. consistent/cautious)
2. Conscientiousness (efficient/organized vs. easy-going/careless)
3. Extroversion (outgoing/energetic vs. solitary/reserved)
4. Agreeableness (friendly/compassionate vs. challenging/detached)
5. Neuroticism (sensitive/nervous vs. secure/confident)

Learning Style Identification: To identify the learning style of a particular student, among multiple psychology theories available, Index of Learning Style Inventory also known as the Felder and Silverman's learning style model is built based on the Kolbe's Learning Style Inventory. The Index Of Learning Style Inventory (ILS) has four spectrum of learning style including:

1. Sensing-Intuitive
2. Visual-Verbal
3. Active-Reflective
4. Sequential-Global

Data is being collected from around 80+ students through the web interface. All the responses are being predicted separately. Among the 44-questionnaire, 11 questions each belong to one of the four spectrums of the Index of Learning Style theory. Each question has 2 options only. Based upon the answers given by the student for each category, the dimension in which the student will fall will be calculated. The former logic is carried out with the help of python.

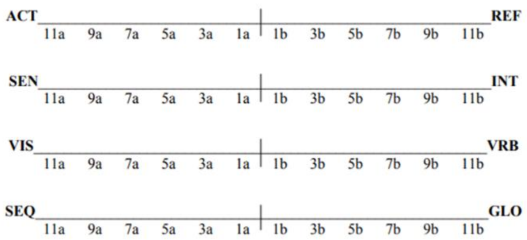

Figure 2:ILS Scaling

The report works as if a pupil is considered to be relatively even on the two dimensions of a scale if their score falls between 1-3. If a student's score is between 5 and 7, they have a considerable affinity for one of the scale's dimensions and will learn more quickly in a setting that favors that feature. If a student receives a 9 or an 11 on a scale, they strongly prefer one of the scale's dimensions. In a setting that does not accommodate their preferences, students can have significant trouble learning.

Mapping & Recommendation: The personality trait and learning style of a particular student is identified using Five Factor Model and Index of Learning Style theory respectively as soon as the student submits the test. From this, the personality and learning style of an individual is correlated, in order to give suggestions on the learning strategies to be followed along with the corresponding e-learning platforms. The recommendation mainly focuses on e-learners. With the recommendation provided, the students could take it as a suggestion to improve their learning strategies and academic performance. The recommendation is done through the web interface which is built using flask framework. The frontend is built using bootstrap, CSS and JavaScript.

4. METHODOLOGY

Here project is to build a web interface with two sets of questions for the student to complete in order to understand and learn more about his/her personality traits and learning style. So that they can enhance their learning methods and have a better understanding of themselves, which in turn suggests learning tactics and e-learning platforms. This project consists of 5 modules, which are to be completed to implement.

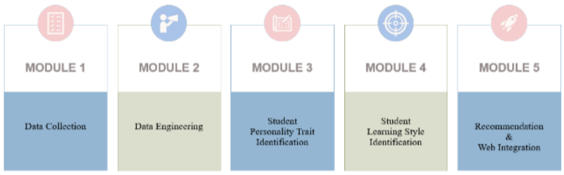

Figure 3: Module Diagram

In order to identify the user's personality trait and learning style two sets of questionnaires were utilized, Big Five Personality Trait Inventory and Index of Learning Style Inventory (Felder-Silverman) were used correspondingly. This Data is collected through a web interface that will be circulated among the students.

The Big Five Personality Test, also known as the IPIP NEO (International Personality Item Pool Neuroticism-Extraversion-Openness) is a well-known personality assessment tool based on the Five Factor Model of Personality. The IPIP NEO is a self-report questionnaire that consists of 50,60,120 and 300 items. As of the project a 50-item set questionnaire is used, which is with 10 items measuring each of the five personality dimensions. The test takes around 15-20 minutes to get the result, where response scale was labelled between 1 to 5 from strongly agree to strongly disagree.

Index of Learning Style Inventory (Felder-Silverman), which is a 44-item questionnaire whose response will lie between 2 options only. The Felder-Silverman learning styles model has four dimensions to evaluate preferences on each one.

The personality trait and learning style of a particular student is identified using Five Factor Model and Index of Learning Style theory respectively as soon as the student submits the test. From this, the personality and learning style of an individual is correlated, to give suggestions on the learning strategies to be followed along with the corresponding e-learning platforms. With the recommendation provided, the students could take it as a suggestion to improve their learning strategies and academic performance. The recommendation is done through the web interface which is built using flask framework. The frontend is built using bootstrap, CSS, and JavaScript.

Learning Strategies Mapping:

In paper [3], correlation analysis between each of the Big Five Personality Traits and each form in dimensions in the Index of Learning is done. Its concluded analysis result suggests that,

(a) The Active-Reflective learning styles of e-learners were positively connected with the Openness personality characteristic.

(b) The Sensing-Intuitive learning styles of e-learners were positively connected with the Conscientiousness personality trait.

(c) Agreeableness was inversely correlated with all other learning styles, but positively correlated with active, sensing, visual, and sequential learning.

(d) Extraversion and each of the four learning styles were positively correlated.

(e) The final finding showed that all four learning styles and neuroticism had a negative correlation.

So, the suitable Learning strategies to enhance a student's Learning methodology is suggested according to which learning form they fall into . Also, as of Personality trait, all students will have all these traits but which dominant trait cluster they belong helps them understand about themselves and the right way of learning methods.

5. IMPLEMENTATION

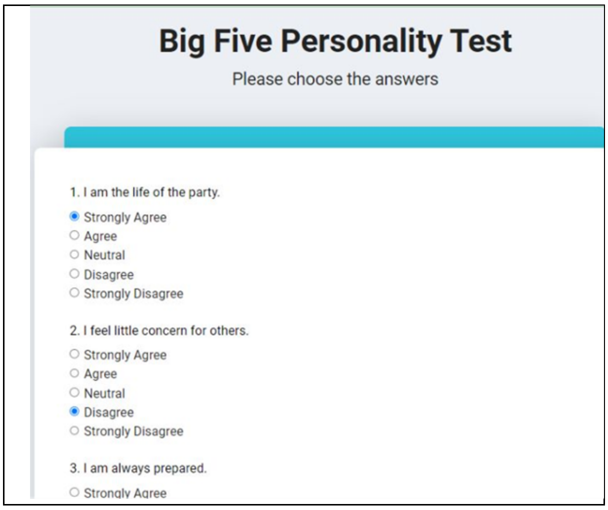

Figure 4: Big 5 questionnaires

Figure 4 shows the view of the UI Page to collect responses from the students for the big five personality trait clustering.

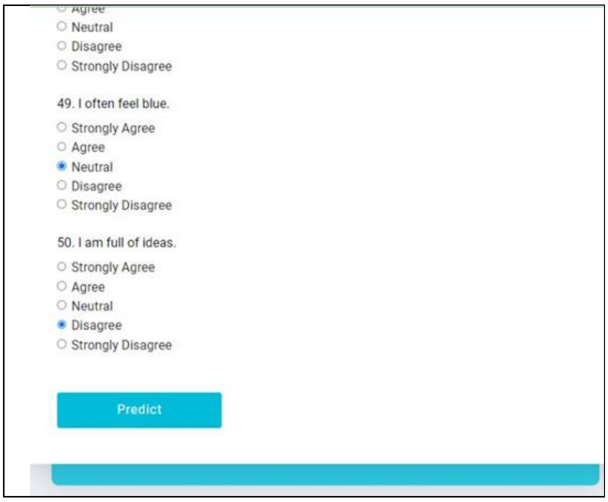

Figure 5: Big 5 Prediction End Page

Figure 5 shows the end of the Big 5 questionnaire page. Here once the user clicks Predict, these responses are taken into the background running ML model to predict the right cluster among the 5 clusters.

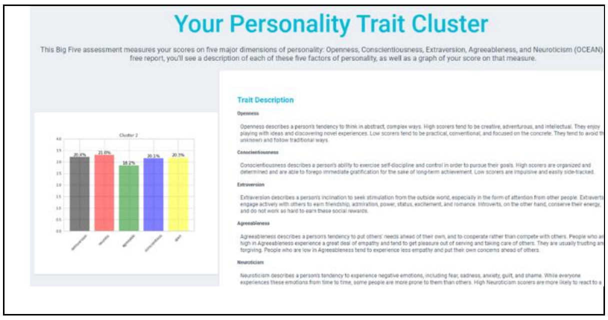

Figure 6: Big 5 Result Summary Page

The above Figure 6 is the result summary with each trait description. For big five clustering, k -means Clustering is used, as it's the one of the most famous models under the realm of Unsupervised Learning in Machine Learning. KElbowVisualizer is used to find the correct k value for clustering. Where The k-Means algorithm is used to cluster the personality traits into 5 groups. From the elbow, it can be seen that number of clusters=5, which looks optimum for the dataset. Also, the number of clusters needed or appropriate is also 5. Then the users' responses are clustered into 5 personality clusters, where each cluster has 5 different combinations of each personality trait. These clusters are visualized as bar graphs by taking the mean for each cluster. Then for incoming responses the model predicts the cluster.

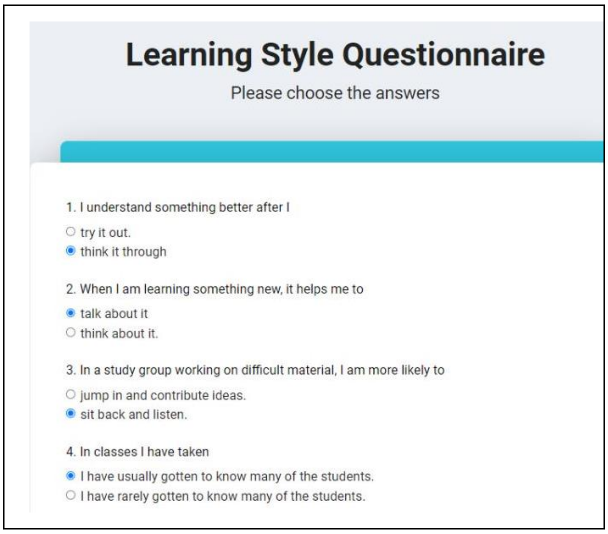

Figure 7: ILS questionnaire page

Figure 7 shows the Page that collects responses from the students for identifying their learning style using Index of learning style Inventory.

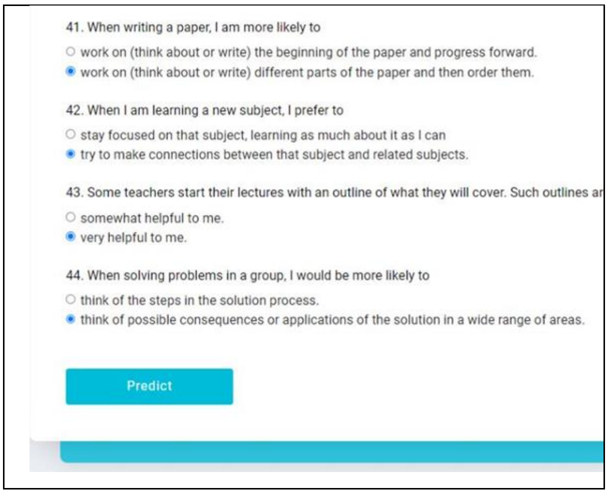

Figure 8: ILS Prediction End Page

Figure 8 shows the end of the Learning style page. Where here, Once the user clicks Predict, these responses are taken into the background running python code to find the learning style for each dimension.

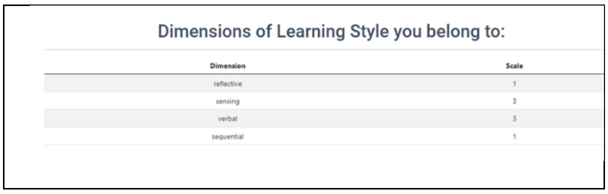

Figure 9: ILS Result

Figure 9 shows the student 's scale for each dimension along with the dominant learning style in the corresponding dimension.

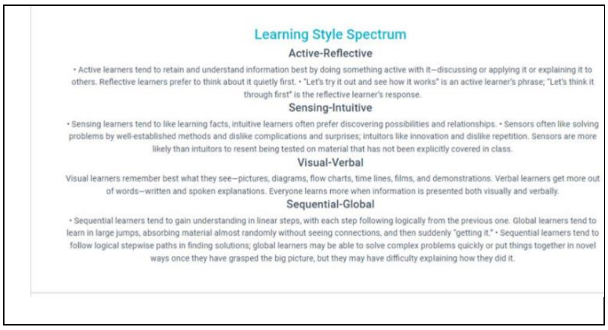

Figure 10: ILS Spectrum Description

As shown in Figure 10, for users to better understand what these 4 dimensions of two learning styles each mean, each dimension learning style description is given.

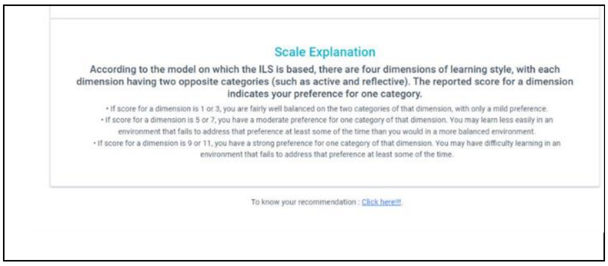

Figure 11: ILS Scale Explanation

As shown in Figure 11, for users to better understand what learning style that they belong to in each dimension score explanation is given.

Figure 12: Recommendation Learning Strategies

The ideal way to learn is individually for each learner. The quality of learning can be increased by identifying and understanding one's learning preferences. Several learning style classifications have been created by numerous studies. But A widely used Model called Index of learning style is taken. So as shown in Figure 12 show the recommendation page for how to enhance their learning styles, where closely suited learning strategies are suggested along with Big five Cluster explanation.

6. RESULT DISCUSSION

For Personality trait identification, The Big Five personality traits, also known as the Five Factor Model, is used. In the context of the Big Five personality traits, clustering refers to the grouping of individuals based on their rating on each of these five dimensions and which can be helpful for comprehending how people with similar personality qualities may behave, think, and feel in various circumstances and help individuals understand their personality better.

The Big Five qualities can be used to cluster individuals into groups using a variety of techniques, such as principal component analysis (PCA), hierarchical clustering, and K-means clustering. Each of these approaches has advantages and disadvantages of its own and can yield various outcomes. K-means clustering is used, and the individuals are clustered into 5 clusters. As of Elbow Visualizer 5 clusters look optimum for the data set.

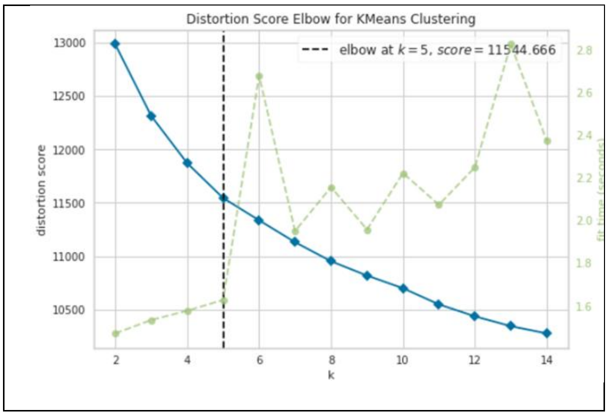

Figure-13 Elbow Visualizer for Big Five K-means Clustering.

Figure 13 is a graphical representation of the elbow approach, which is a well-liked machine learning method for figuring out the best number of clusters to employ for a specific dataset. By charting the proportion of variance explained versus the number of clusters employed, an elbow plot, also known as an elbow visualizer, can be used to determine the ideal number of clusters.

To score a K-means model, different metrics are used based on the specific problem and dataset. Here 3 different common measuring metrics are calculated in order to find the best K-mean model in this testcase.

1. **Within-cluster sum of squares (WSS):** The most popular statistic for assessing K-means models is within-cluster sum of squares. It adds up the squared distances between every point and the center of the cluster to which it is assigned before summing these values for all clusters. This value represents how closely the points in each cluster are crowded together, and the objective is to minimize it.

2. **Calinski-Harabasz index (CH):** This metric counts the difference in variance across clusters and within clusters. A higher value denotes improved clustering.

3. **Davies-Bouldin index (DB):** This metric measures the average similarity between each cluster and its most similar cluster, relative to the average dissimilarity between each cluster and its least similar cluster. A lower value indicates better clustering.

Table 1 Different K-means model with Metrics

No of Clusters	WSS Score	CH Index Score	DB Index Score
2	67276332.76	71106.04	2.87
3	63863692.55	91054.43	2.83
5	59909120.34	115553.85	2.73

Based on the above Table 1, K-mean model with no of clusters = 5 has been selected, since it's validation scores as of Within-cluster sum of squares is minimum comparatively to other K-mean models with different K-value as well as its Calinski-Harabasz index is of higher value and Davies-Bouldin index is of lower value when K value is equal to 5.Which indicates better clustering.

For Learning Style identification, The Index of Learning Styles (ILS) is used, a self-report instrument designed to assess an individual's preferences for 4 learning styles dimensions. The ILS Scoring Sheet is used to score the responses and calculate the scores for each learning style preference.

As for Learning Style Strategies, the recommendations are fixed for each learning style. Where these Strategies are added on suggestions that help the user with enhancing their learning methodology. These are psychological research strategies [11].

7. CONCLUSION

The goal and projected contribution of this proposed methodology are to provide new functions to the Educational Recommendation System, making recommendations that are better suited to each student's profile, supporting learning and competency development, and decreasing the effort required of the student to select the best learning resources. In domains of knowledge other than education, such as the recommendation system, personality traits have been applied (tourism, e-commerce, etc.). Use of Big five personality and Index of Learning style get mostly positively correlated so on using these as new functionalities to the filtering system helps students/learners understand better of themselves and one or the other way helps them learn things their appropriate way and good understanding. Such a change in the filtering method should allow the use of diverse referrers in various learning environments, both in formal and informal education, to improve suggestions to students. Further the personality trait theory and learning style need to be analysed and mapped for better recommendation to the students.

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