

Towards A Strategy for Developing a Project Partner Recommendation System for University Course Projects

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Abstract—Project Partner preferences, and the breakdown of team projects has been a challenge both in industry, and university settings. While the consequence is severe in industrial settings, the loss of time, and invested effort in scenarios where university course project breaks down leads to distrust among members and eventual failure in some cases. Thus, it becomes necessary, the acquisition of Collaboratory skills which according to literature is acquired via collaboration with partners whose behaviors cancel out each other's eccentricities. To this end, industry stakeholders have invested enormous resources on the development of user predictive models that optimally predict the outcome of a collaborative engagement. While this strategy is effective, government policies restrict its implementation in institutions of higher learning, thus making collaboration modelling challenging. Ergo, the objective of this endeavor investigation of noninvasive strategies for eliciting individual preferences that affect collaboration and the development of study recommendation partner system. Consequent on the literature review, we have employed a big five-oriented questionnaire input which is passed through a personality based similarity system based on collaborative filtering and utility-based recommendation system. Findings show that generated teams are academically balance which is the main objective of the study recommendation partner system.

Index Terms—Recommendation Systems, Big Five, Collaboration in Teams

I. INTRODUCTION

In recent times, recommendation systems have become extremely common as it facilitates the discovery and accessibility of choices or options that ordinarily will be difficult to access. Thus, the commercial has invested significantly in the research and development of different varieties of these systems. This has not been the trend in the educational sector. In the course

of an academic semester, student are normally requested to form project groups. Withing these groups, some thrive in collaborative settings, while others work best alone. Thus, it becomes important, the knowledge of how team members dispositions, what they value most, their strengths, their weaknesses, and their communication style. As it can potentially assist teams in being more productive. It is also a frequent occurrence that teams break down as a result of individual differences in personality and decision-making, which ultimately results in the failure of the assigned responsibilities, and tasks. Thus, it becomes necessary, a team member recommendation system for course projects. Several past efforts have been made at creating questioners, and models that near accurately elicits an individual's personality. One of such is the Big Five personality model [1].

The Big Five personality model [1] based questionnaire is implemented to learn about and assess the individual's personality based on their self evaluation with respect to a batch of questions and puzzles [2]. The responses are weighted using likert scales that evaluate whether they strongly agree to strongly disagree to a particular question. The individual's responses are then summed up to derive a score. These scores will indicate the effect a given individual's deposition, or personality, will have on a team collaborating on a course project. We will give more details on this in later sections. The information derived from questioners is then fed into a recommendation system.

Basically, there are three approaches employed in implementing a recommendation system: collaborative filtering, content-based filtering, and hybrid approaches that eliminate the drawbacks of individual methods. Collaborative filtering is based

on the premise that people are not likely to change their past choices concerning past interests. Thus, future recommendations on new items are generated based on how similar these items are to past preferences. Content-based filtering approaches are based on a characterization of the object to be recommended, and the user's preferences. We found collaborative filtering to be a more effective recommendation system, as it allowed the classification of potential team members based on human behavior scores [3]. Thus, students that share similar personality types are grouped to work together. This strategy is further reinforced by literature. [3].

In general, We consider we derive an individual student's academic scores and a threshold academic score. Applying utility-based recommendation, students are grouped into teams in such a way that the final team falls within the range of the threshold academic score [4]. The paper proceeds as follows. The next section introduces studies related to our work. Section III deals with the implementation of our system, and section IV provides insight into our algorithm. In section V, we describe the system schematic. In section VII, we propose strategies for improvement, and in section VIII, we summarize our contributions, and indicate directions for future efforts.

II. RELATED STUDIES

The commerce and industrial sector has seen the deployment of several recommendation systems. While this is not the case in the educational sector, recent adoption of the flipped, and full online learning instructional model has created a demand for project partner recommendation systems. Thus in the following, we summarise the state of the art implementations and related proposals.

Wenting et al., [5], proposed and studied the problem of recommending activity partners to web-users. In their study, their participants were shown how to leverage readily available data on activity attendance preferences from users in their circle, the social context of potential activities, and respective historical preferences. Their proposed methodology leverages past partner knowledge of users. Their findings, elicited via questionnaires, indicate that real users have great interest receiving activity recommendations. Compared to our strategy, we employ the big five personality models for the elicitation of potential partner personality. We then recommendation is generated by matching personality attributes that foster academic engagement. Asabere et al. [6] merged collaborative filtering based on user, and their social relations to recommend conference presentation session venues.

Yang et al., [7] proposed a social recommendation system to assist undergraduate students in their effort to find research project teams in an academic collaboration network. The system creates students profiles from their curriculum vitae, and known social connections in an academic collaboratory network. Using this profile, unsuitable research projects are filtered out recommended, leaving choices that match the students' profile. Conversely, our strategy employes sets of standardised questions to elicit latent personality attributes that

are known to influence an individuals behaviour in an academic collaboratory setting in the form of scores. These scores enable the matching and creation of team project groups. A further effort by Manoj et al., [8] proposed an approach to solve the challenge of identifying suitable experts who should be involved in design decision making process in architectural knowledge management. In their strategy, a machine-learning technique, and an ontology-based approach is used to identify design decisions, and respective architectural elements. In the next section, we give a background description for our strategy

III. BACKGROUND FOR OUR STRATEGY

Several strategies have been proposed for the implementation of partner recommendation systems, and vital for the realization of these systems is the elicitation of the behaviour or character of the individuals to whom partners needs to be recommended. Being a self assessment process, the elicitation of an individuals character, several questionnaires have been designed to near accurately characterize and individual. Chief among them are the big three, and big five personality models. In comparison to the big three models, the big five personality model gives a clearer classification of an individuals personality because it recognizes broader traits of a person, namely neuroticism, agreeableness, conscientiousness, extraversion, and openness [9], [10]. These characteristics broadly encompass most of the narrow traits. Big five personality models utilize lexical sampling and are better reflective of a person's group interactions and socialization. [1] Marvin Zuckerman conducted a comparative study between the big three and big five models using questionnaire reliability assessment and factor analysis, which revealed that conscientiousness is positively correlated, and forms the basis of human social interaction [1], [11]. While there were efforts in the area of intelligent quotient tests, mathematical and reasoning questioners that gives insight on an individual's overall ability to adapt to new situations. The emergence of emotional quotient (EQ), creative quotient (CQ), and other quotients demonstrated that IQ is not the only basis for understanding human behavior in a given situation. Furthermore, "The Complete Book Of Intelligence Tests" by Philip Carter [2], uses questionnaires to identify various types of intelligence. Our questionnaire is based on this literature, and is mapped to the big five personality models [12]. Toughness and tenderness questioner [12] are associated with agreeableness, while optimists and pessimists are associated with neuroticism. Openness is related to both success and risk. Managing people and resources is frequently regarded as conscientious while extraversion is linked with communication and role [2]. In general, human behavior and personality are inextricably linked, and people's interests and tastes are frequently the results of their personality or consistent behavior. Teamwork is closely associated with personality. Individuals with similar personalities are likely to share interests and behaviors. As a result, they are more compatible with working in a collaborative environment [3]. This serves as the foundation for our collaborative filtering-

based recommendation system, which groups students with similar personality traits to collaborate more effectively and deliver the desired results.

A. Big Five Personality Traits

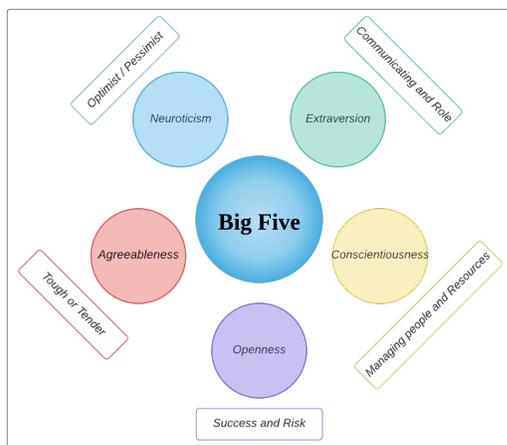


Fig. 1: Big five personality traits with questionnaire [13]

The big five personality traits have been identified to be more closely related to academic performance [14]. According to the Big Five personality predictors of post secondary academic performance, these five characteristics have a positive or negative correlation with academic performance [15]. The results show that conscientious students perform better academically than those who are not conscientious due to their motivation. Because of emotional instability, neuroticism has been found to be negatively associated with academic performance; however, this is not the case for students who have a healthy mindset. Openness and extraversion produce mixed results, with extraversion influencing student performance when classroom engagement is required [16]. According to the findings of the study, agreeableness is not a significant predictor of a student's academic performance, implying little correlation with academics [17].

The questionnaire is created using specific characteristics that correspond to the big five personality traits.

- **Extraversion** - One of the Big Five personality qualities is extraversion. It is linked to those who are outspoken, friendly, and assertive. Sometimes it has no effect on students' behavior, depending on the situation [18]. A form of questionnaire that is related to extraversion is the communicating and role questionnaire. Students who perform better on this section are more extroverted than those who score low [19].
- **Neuroticism** - Being emotionally stable is a trait known as neuroticism. It shows that emotionally healthy students outperform emotionally unstable students in the classroom [17]. This trait is related to the optimist and pessimist questionnaire. Students with better scores have a tendency to be more optimistic and have a positive

outlook for the future than students with lower scores [2].

- **Agreeableness** - Being agreeable is one of the attributes that shows if a person is kind and courteous. It is linked to whether pupils act in a tough or sensitive manner. Despite the fact that there is some connection to academia [17]. Additionally, it affects how a team is formed and how well it performs. Students who scored lower in this part are tender, whereas those who scored better overall are tougher [2].
- **Conscientiousness** - Conscientiousness reveals a person's level of organization and discipline. Additionally, it has been discovered that students with higher levels of conscientiousness surpass those with lower levels in terms of academic performance [17]. Additionally, it demonstrates the strongest correlation between all five personality characteristics [17]. Managing people and resources is covered on the conscientiousness questionnaire. Students who score higher on this part of the questionnaire are classified as conscientious [20].
- **Openness** - Openness is a sign of a person's receptivity. It reveals whether someone is willing to face challenges and take risks. This element has only had a minor effect on how well students work together as a team [17]. Success and risk assessments are included in this wider Big Five model trait. Higher scorers on this questionnaire are more inclined to take chances, and vice versa is true for lower scorers [2].

Cold start problems are frequently associated with collaborative filtering (CF), but using CF to recommend teams based on personality assessment overcomes this limitation. According to this approach, human behavior is strongly intertwined with its decision-making pattern [21]. This demonstrates the interdependence of personality, decisions, learning preferences, and interests [3], [22]. In the proposed collaborative filtering of students' responses for personality, assessments are stored in the form of a vector and processed to provide a team recommendation [23].

IV. IMPLEMENTATION

Our strategy is a two part technique. In the first technique, we use a collaborative filtering (CF) recommender system technique as it is the most widely used recommendation method [3], and highly suitable for our context, where a student's personality profile serves as input, for similarity evaluation with other students personality profile. We further employed the unsupervised machine learning algorithm, K-Nearest Neighbors (KNN), as there was no labeled data available due to privacy concerns. Thus using the strategy, we generated a student similarity matrix for the CF recommender [24]. In the second technique, Utility-based (UB) recommender system with a utility function that predicts academic scores based on student personality profile is a used while we use collaboration filtering recommender system as a baseline for comparison as it does not take personality-based academic performance

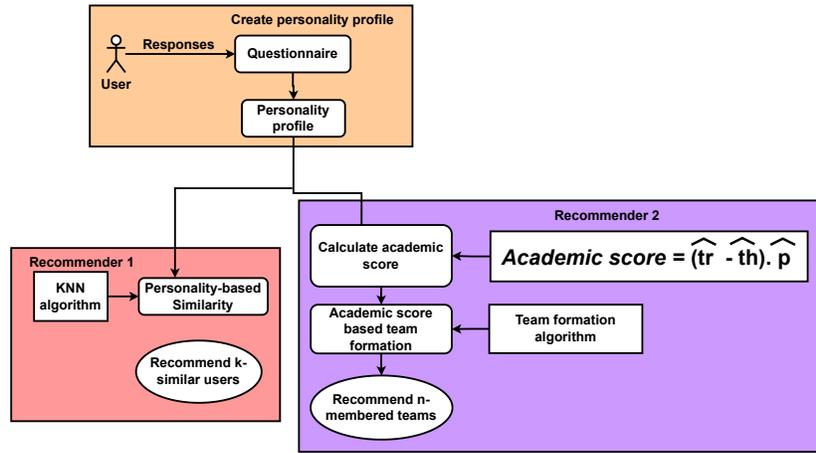


Fig. 2: Recommendation Methodology

into consideration. To measure utility where multiple attributes are responsible in decision making, we formulated a Multi-Attribute Utility (MAU) function [25].

A. Method description

The process of generating recommendations using the student's personality questionnaire responses is depicted in Fig 1. As shown in Fig 1., the CF recommender and UB recommender are named Recommender 1 and Recommender 2 respectively.

• Build Student Personality Profile

Big 5 questionnaires are used to collect student responses. student responses are given scores from 1 to 5 and accumulated to calculate the student's traits score. Different ranges of scores are provided by researchers to identify qualities and narrow traits. Threshold, 50% of total trait score, helps in classifying the genetic trait of the student example, optimist or pessimist [2]. The student personality profile is complete once response scores are assigned and trait scores are calculated and stored in memory, as shown in Fig 3.

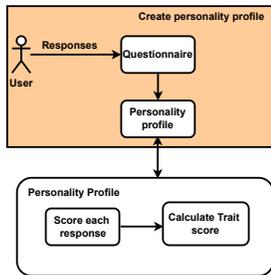


Fig. 3: Build Student Personality Profile

• Recommender Systems

The software technique which we are using to suggest items is known as Recommender Systems. Here, items that are being recommended are a team or members of the team.

Recommender 1: Collaborative Filtering Recommender System

CF recommender system is the baseline recommender system, as it is depicted in Fig 4. CF recommender system works by finding similarities in students' response patterns and recommending students with high similarity scores to be on the same team. KNN algorithm, an unsupervised machine learning technique, is used to create a similarity score matrix. The cosine similarity function is selected to calculate the similarity score. As KNN algorithm works with vectors, thus student response vector is fetched from student personality profile's response scores. Considering each response score as one dimension, a high-dimensional vector for all the students is formed and fed to the CF recommender system. Vector dimensions are equal to total questions [26].

Student response vector:

$$response = [tr1_res1, \dots, tr1_resN, tr2_res1, \dots, tr2_resN, tr3_res1, \dots, tr3_resN, tr4_res1, \dots, tr4_resN, tr5_res1, \dots, tr5_resN]$$

where, $response$ = response vector of a student, trN_resN = Nth response score of Nth Trait of a student.

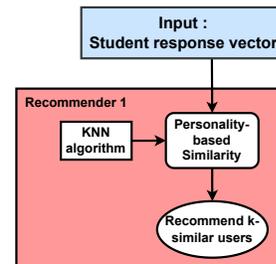


Fig. 4: Recommender 1: Collaborative Filtering Recommender System

Each student will receive recommendations of k other

students who have a high degree of similarity based on their response scores.

Recommender 2: Utility-Based Recommender System

On the other hand, the UB recommender (Fig 5) takes the student's trait scores and calculates an academic score for each student using the utility function (f).

Student trait score vector:

$$\vec{trait} = [trait_scr_1, trait_scr_2, trait_scr_3, trait_scr_4, trait_scr_5]$$

Threshold vector:

$$\vec{threshold} = [threshold_{trait1}, threshold_{trait2}, threshold_{trait3}, threshold_{trait4}, threshold_{trait5}]$$

Correlation vector:

$$\vec{\rho} = [\rho_{trait1}, \rho_{trait2}, \rho_{trait3}, \rho_{trait4}, \rho_{trait5}]$$

Academic score:

$$f = (\vec{trait} - \vec{threshold}) \cdot \vec{\rho}$$

where, \vec{trait} = trait score vector of a student, $\vec{threshold}$ = threshold of each trait, $\vec{\rho}$ = academic and personality trait correlation [4].

A team formation algorithm is used to form k-member teams with similar academic score averages. This k-member team is later recommended to the student. The deviation used by this algorithm is determined by trait and threshold. Furthermore, the product of the trait vector and correlation is used to determine academic score. A recommendation is made to create a balanced team based on each student's academic scores. Here, the academic score is taken from the previous algorithm and a team size is specified. This algorithm uses statistical means based on the calculated academic scores to formulate teams with similar scores.

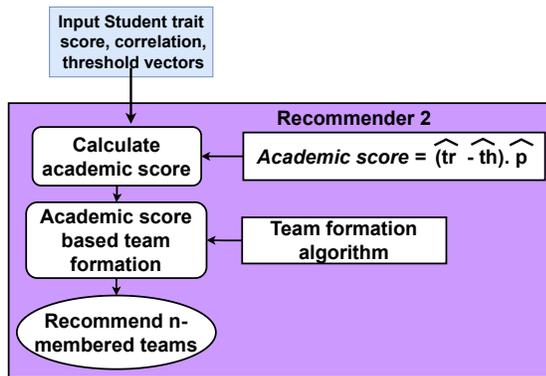


Fig. 5: Recommender 2: Utility-Based Recommender System

V. ALGORITHM DESCRIPTION

Algorithm 1 Utility function: Academic score algorithm

Require: \vec{trait} , $\vec{threshold}$, $\vec{\rho}$
 1: $deviation = \vec{trait} - \vec{threshold}$
 2: $Academic_Score = \vec{trait} \cdot \vec{\rho}$
 3: **return** $Academic_Score$

Algorithm 2 Team formation algorithm

Require: Dictionary {student: Academic_Score}, team_size
Ensure: $length(Dictionary) \neq 0$
 1: Initialize list all_teams
 2: **while** $length(Dictionary) > 0$ **do**
 3: Initialize lists team and scores
 4: $mean_tolerance = 0$
 5: $total_mean \leftarrow mean(Dictionary)$
 6: team append key.Dictionary[0], scores append value.Dictionary[0]
 7: $DeleteDictionary[0]$
 8: **while** $(length(team) > team_size) \ \& \ (length(Dictionary) > 0)$ **do**
 9: scores append next value.Dictionary[0]
 10: $mean_score \leftarrow mean(scores)$
 11: **if** $mean - tolerance \leq mean_score \leq mean + tolerance$ **then**
 12: team append key.Dictionary[index(0)]
 13: Delete key and value of Dictionary[index(0)]
 14: break
 15: **else**
 16: scores.pop()
 17: **end if**
 18: **end while**
 19: **if** $length(team) \text{ no change}$ **then**
 20: increase tolerance
 21: **end if**
 22: all_teams append team
 23: **end while**
 24: **return** all_teams

VI. SYSTEM SCHEMATIC

The several tools and technologies utilized are Visual Studio, PHP, CSS, JavaScript, Bootstrap, and Python Libraries to deliver the optimized web application to the students.

We implemented the accessibility of the web application for administrators and students. The implementation diagram of the system is shown below.

A. Administrator accessibility

The admin has a dashboard that shows the total number of students and recommended teams, as well as access to all student details. Administrators have more privileges than students, such as the right to modify, create, or delete questionnaires for all the categories i.e. Tough or tender, Optimist or pessimist, Success, and Risk, Communicating and Role,

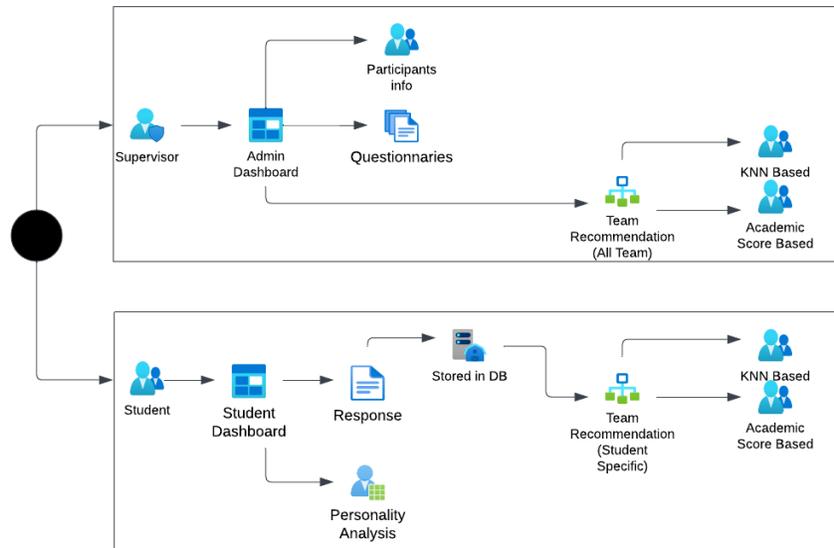


Fig. 6: Schematic representation of implementation

and Managing people and resources [2], [27]. Admin can also visualize all students' personality assessments in the form of radar graphs and academic scores. Via the SQLValidator [28], The supervisor has access to each of the recommended teams based on both recommendation techniques.

- **Admin dashboard** - The total number of students registered in the web application is displayed on the admin dashboard; this information is relevant to estimate the number of students who have registered and want to participate in the questionnaire. It also includes the number of teams that have been suggested using utility-based filtering. It keeps track of the number of teams that are specifically created with participation from every student based on their academic performance.
- **student dashboard** - The student dashboard, which is linked via the admin dashboard's students tile, and can also be accessed from the sidebar menu contains information about all registered students, including their names, email addresses, and calculated academic scores.
- **Teams** - Collaborative filtering and utility-based recommendations are the two forms of recommendations that have been employed in teams. One recommendation includes the students' recommendations for a specific student based on their questionnaire responses. It brings together the students with comparable personality traits. As a result, a single student may receive several similar student recommendations. To access the radar map of the student for whom the recommendation is made, an action button is also provided for the admin in this dashboard.
- **Radar chart** - Based on the types of questionnaires that have been used, this radar is created using the big five personality traits. It displays a graphical representation of

Name	Email	Academic Score
student1	stu1@gmail.com	18.3500
student2	stu2@gmail.com	2.2800
student3	stu3@gmail.com	4.0700
student4	stu4@gmail.com	3.8000
student5	stu5@gmail.com	2.9300
student6	stu6@gmail.com	4.9100

Showing 1 to 7 of 7 entries (filtered from 6 total entries)

Previous 1 Next

Fig. 7: Academic score of all students : Admin View

the student's personality. These tests are divided into five categories. For each questionnaire, the students' weighted responses are stored. For each category of the questionnaire, the student input is normalized and graphically shown.

The implementation of utility-based filtering is a further recommendation. It has been recommended based on academic performance in order to create a balanced team that can successfully execute the team project. This recommendation is unique because it has been produced in order to meet the team's academic score threshold,

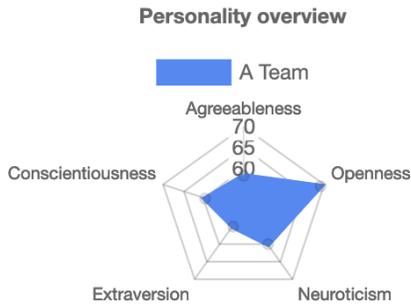


Fig. 8: Personality Overview: Radar Chart

taking into account all the students.

- **Questions** - Administrators have extra privileges in the question's dashboard that let them edit and remove already-existing questionnaires, as well as add new ones to the list. This gives the administrator additional flexibility to broaden the scope of the questionnaire.

B. student accessibility

Students' privileges are rather limited, as they can only fill out questionnaires and receive their own personality assessment in the form of radar charts. A student's visibility is limited to teams that are linked to that student for both recommendation techniques.

- **Personality overview** - After logging into the account, the dashboard presents a radar graph of that individual student's personality assessment based on questionnaires of the big five personality.
- **Team** - It is a menu that displays recommendations determined through collaborative filtering and utility [29]. The only difference in this scenario is that just the teams with the specific logged-in students are displayed. The list of all the teams for both suggestions is only visible to the admin.
- **Questionnaire** - This is a list of all the questions the administrator has included in the questionnaires. Students are not informed of the category that a given question belongs to. Students can choose between strongly agreeing and strongly disagreeing in their responses [30]. As soon as the students have marked each questionnaire, the responses are saved. These responses are afterwards quantified and analyzed in order to recommend a particular team.

C. Team generation

The team is generated by a python script in the back end. The admin generates this after all students have completed the questionnaire and their individual assessments are available to the admin. To provide optimal teams, we used two types of recommendation methods that took into account individual personalities and academic scores.

VII. EVALUATION AND RESULT

Both recommendation systems are implemented independently of one another, taking into account different factors and producing results for the team recommendation. Both have merits and drawbacks. The collaborative filtering recommendation provides a list of k similar students who can collaborate constructively [3]. This filtering has a high dimension because it considers all five major personality traits as well as student responses, thereby taking into account inherent human behavior and attitude. However, this is not associated with the student's academic performance. It is entirely determined by their personality assessment. As a result, based on personality assessment, a single student can have multiple recommendations with whom it is closely related. As a result, the student has more options for selecting teammates. This provides dependability in terms of team collaboration.

Name ↕	Email ↕	Recommended Name ↕	Recommended Email ↕	Action ↕
student1	stu1@gmail.com	student6	stu6@gmail.com	
student1	stu1@gmail.com	student2	stu2@gmail.com	
student1	stu1@gmail.com	student4	stu4@gmail.com	
student1	stu1@gmail.com	student5	stu5@gmail.com	
student1	stu1@gmail.com	student3	stu3@gmail.com	
student2	stu2@gmail.com	student1	stu1@gmail.com	
student2	stu2@gmail.com	student4	stu4@gmail.com	
student2	stu2@gmail.com	student6	stu6@gmail.com	

Fig. 9: Recommender 1: Collaborative filtering Recommender results

Utility-based recommendation ranks teams solely on academic performance. This means that the recommended team is academically balanced. However, it does not take into account the students' personalities. As a result, this takes narrow aspects into account. This recommendation provides unique teams based on individual academic scores, limiting students' options for team selection. The main advantage of this team is that the team's overall threshold academic score is balanced. As a result, it provides dependability in terms of task completion.

VIII. SUMMARY AND FUTURE WORK

In this paper, the investigation on the relationship between academics, and personality is conducted, and research findings led to the formulation of a utility function that predicts academic performance based on student profile built using the Big 5 personality model. To evaluate the utility-based recommendation system, we first implemented a baseline collaborative filtering recommender, and the results of both recommenders were discussed. A major challenge in the evaluation was the

id	Team
1	student1(stu1@gmail.com) student2(stu2@gmail.com) student6(stu6@gmail.com)
2	student3(stu3@gmail.com) student5(stu5@gmail.com) student4(stu4@gmail.com)

Showing 1 to 2 of 2 entries

Previous 1 Next

Fig. 10: Recommender 2: Utility-Based Recommender's Result

lack of a labeled dataset because of privacy concerns. This challenge resulted in performing only functional and meta-comparisons between the two recommender systems. Our future work consists of optimizing academic correlations using reinforcement learning, and improving academic performance perdition by adding more impacting features.

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