Personality-Aware Decision Making In Educational Learning

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ABSTRACT

Personality, as one of the human factors, has been demonstrated as an influential element in decision makings. Its impact in educational learning is still under investigation and there are very few of available data sets in this area. In this paper, we introduce one data that is collected from user studies, describe our exploratory analysis and discuss the corresponding research topics. Furthermore, we encourage more discussions or ideas about the data collection, experimental design, promising topics and research challenges.

CCS CONCEPTS

• **Human-centered computing → User models**; • **Information systems → Recommender systems**;

KEYWORDS

decision making, personality, educational learning

1 INTRODUCTION

Personality has been recognized as one of the influential human factors [8, 14] in the process of decision making. Researchers come up different frameworks, such as the big five factors [7], to capture the personality traits. Personality-based recommender systems [8–10] have been built to better assist both individual and group decisions. However, there are very few of data available for public research in these areas, especially when it comes to the educational domain and the topic of group decision making. The motivation in our work is to contribute such a data, discuss promising research topics and encourage different types of research on personality-aware decision making in the educational learning.

2 DATA COLLECTION

We are seeking a data from the educational domain which include human factors, individual and group preferences to explore the impact of personality in group decisions. However, there are no such a data available for research. We decide to collect the data by our own. We have several courses in our department which require students to complete a practical project at the end of the semester. Students have their own choice to select the topic of the project, and they can complete it individually or by a team work. We ask student volunteers to fill the questionnaires to collect the data:

- **Topics of The Projects**: The "items" in the study are the topics of the projects. Currently there are three courses involved in this study: a database, a data analytics and a data mining class. Students are required to complete a development project (e.g., Web-based information system with database connections and operations) for the database class, and a data science project for the other two classes. Take the data mining or data analytics class for example, we provide the information about 50 data sets that are available on Kaggle.com. Students should understand the data and figure out research problems, as well as solutions by themselves. In terms of the database class, we provide a list of 20 real-world examples to give them some ideas, e.g., e-commerce site like Amazon.com, online streaming system like Youtube.com, and so forth. In future, we may add more topics of the projects, and randomly present a number of them to the students.
- **Individual and Group Preferences**: Initially, each student is required to select at least three liked and disliked projects. They are asked provide an overall rating and multi-criteria ratings (e.g., ratings on App, Data, Ease) to each project. If they decide to complete the projects by team work finally, each group needs to fill in the survey again by group discussions. By this way, we are able to collect both individual and group preferences associated with multi-criteria ratings.
- **Demographic Information & Personality Traits**: We additionally collect students' demographic information (e.g., age, gender, marriage status, country, etc) and personality traits. We use the Big5 framework [7] to collect the personality traits in form of *Openness (O), Conscientiousness (C), Agreeableness (A), Extraversion (E), Neuroticism (N).* The well-known Ten-Item Personality Inventory (TIPI) [4] is adopted in the user study as the questionnaire to collect the personality traits.
- **Learning Behaviors**: In addition, we are also able to collect students' learning behaviours, such as whether they turn on assignments on time, how frequent they resubmit an assignment, whether they watched online videos online, their final choice on the topic of the final project, and so forth. These information potentially could be used to predict user personalities.

3 EXPLORATORY ANALYSIS

The study is still ongoing, while we have collected data for a full year – we have obtained a data set with 194 individuals and 122 groups. 81 out of 122 groups are composed of at least two subjects, while other groups are the ones with only a single member. These individual subjects leave 1951 ratings on the topics of projects, while all of the groups leave 745 ratings in total. The ratings are given to the topics of the projects for all of the three courses.

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We perform basic exploratory analysis and summarize the findings as follows:

Table 1: Comparison of Personality Traits (* indicates significance at 95% confidence level by gender)

		O	C	E	A	N
Overall	Mean	5.22	5.05	4.63	4.85	4.11
	SD	1.28	1.34	1.49	1.47	1.53
Male	Mean	5.15	4.89*	4.52	4.64*	4.12
	SD	1.23	1.38	1.4	1.49	1.44
Female	Mean	5.32	5.27	4.78	5.14	4.1
	SD	1.34	1.26	1.61	1.39	1.66

- We compare individual personality traits for male and female students. The results can be described by Table 1. The significant test reveals that the male students present lower score in conscientiousness and agreeableness than the females.
- The score in openness has significant correlations (> 0.6) with the score in extraversion and agreeableness. The value in the overall rating has strong correlations (> 0.82) with the multi-criteria ratings. There are no significant correlations between personality traits and user ratings on the items.
- Each team is required to fill the survey again to present their preferences on the topics of the projects. We are interested in the ratio of the overlaps based on the selected items by the individual members and the whole group. The average ratio turns out to be 36% only.
- It is interesting to figure out how students select their team members. For this purpose, we examine the similarity of the members within a same group in terms of the similarity in the personality traits and the similarity in their ratings. The result that is shown by Figure 1 tells us that the intra-group similarity in the personality traits is significantly and much higher than the similarity in ratings on the items.

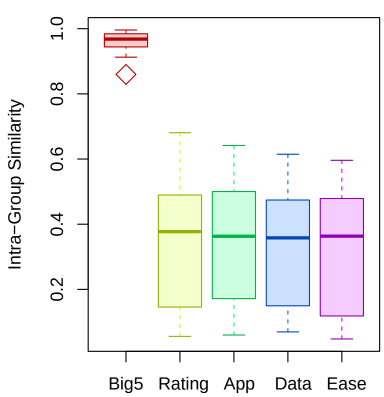

Figure 1: Comparison of Intra-Group Similarities

4 RESEARCH TOPICS

4.1 Personality-Aware Decision Making

The major research topic is exploiting the impact of personality on education learning. The topics of interests may include but not limited to: understand why and how they find team mates, how personality affects the individual and group decisions, what are the different user roles in the groups, and so forth. The learning behaviors in the data potentially are useful to make predictions on user personalities.

4.2 Personalization

The data is available for traditional recommender systems (i.e., recommendations for individuals), group recommender systems (i.e., recommendations for each group) [6], content-based recommendations (by utilizing the topics of the projects) [5], multi-criteria recommender systems (i.e., recommendations based on multi-criteria ratings) [2, 11], context-aware recommendations (i.e., semester, year, course can be viewed as the context information) [3, 13], and multi-stakeholder recommendations (i.e., a balance between students' preferences and instructors' expectations) [1, 12].

4.3 Learning Evolutions

The selection and performance on the projects, potentially will motivate the students to build new learning or career goals. We plan to track a student's learning behaviors and tastes in the topics of the projects, to further understand the evolution of their learning goals and achievements, as well as the associations between personality traits and the evolution. For a long run, the system could be a learning platform which not only assists the selection of the topics for final projects, but also suggests useful learning materials to help educational learning.

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