Enhancing Personalized Learning with MBTI Forecasts and ChatGPT's Tailored Study Advice

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Abstract

Assessing students' learning behaviors has always been a focal point in the field of education. However, traditional assessment methods based solely on grades and learning behaviors often lack personalization, failing to truly understand the root of students' issues. Therefore, this study aims to address this problem by focusing on understanding students' Myers-Briggs Type Indicator (MBTI) personality types. It aims to provide personalized recommendations based on students' learning conditions and personality traits. Ultimately, it intends to suggest suitable study companions for students, enhancing both their learning motivation and efficiency. To achieve this goal, this study utilizes the LBLS467 Database to cluster students, conducts MBTI personality assessments using ChatGPT, offers study recommendations, and ultimately compares similarities to suggest suitable peers for group learning. This approach aims to aid students in their learning within the educational environment.

Keywords

Learning Behavior, Behavioral Analysis, Student Modeling

1. Introduction

Personality traits are a psychological concept that interprets the meaning behind various human behaviors by observing specific characteristics, thus identifying individuals' traits. One of the most popular methods recently is the Myers-Briggs Type Indicator (MBTI) personality analysis. Using machine learning techniques to analyze comments or tweets on social media to predict the author's MBTI personality type lays the foundation for creating a system that identifies people's personalities [1].

Questionnaires are widely regarded as effective tools for data collection in various fields. By analyzing questionnaires, one can identify data distributions and consequently acquire resources that align with their objectives [2]. conducted an analysis using discrete data collected through questionnaires, exploring the impact of variable combinations in questionnaire responses on behavior. Developed a model applicable to various questionnaire datasets for conducting cluster analysis and interpretable inference [3]. Utilized Kmeans clustering analysis on questionnaire data during experimentation, resulting in the creation of an MBTI personality prediction system [4].

After conducting a learning analysis using questionnaires, personalized learning recommendations and teaching guidance can be provided to enhance students' learning efficiency and motivation. Utilized machine learning to analyze student learning data and offering feedback that enables students to self-reflect on their learning activities and promote self-regulation [5].

In addition to a strong learning motivation, peer-assisted learning is also crucial. Conducted an MBTI analysis on employees' community posts to establish their personality traits. This led to the formation of optimal team compositions, creating the most suitable work teams based on identified personality characteristics [6].

Therefore, this study utilized the LBLS467 learning questionnaire and conducted analysis using Kmeans to determine students' MBTI classifications. Based on this, appropriate learning advice was provided. Additionally, recommendations were made for students to engage in mutual learning to achieve collaborative learning objectives. Ultimately, this approach aimed to enhance students' learning motivation and efficiency.

LAK-WS 2024: Joint Proceedings of LAK 2024 Workshops, March 18–19, Kyoto, Japan
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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

2. Methods

2.1 Dataset

The Strategy Inventory of Language Learning (SILL) from the LBLS467 (Learning Behavior Learning Strategy467) dataset, along with students' self-regulated learning (SRL_S) and Motivation (SRL_M) questionnaires, served as the data sources for this study. SILL assesses students' language learning strategies through 48 items, SRL measures students' self-learning conditions with a total of 50 items, and SRL_M provides 31 questions evaluating students' learning motivation.

2.2 Experiment Design

Figure 1 depicts the experimental process. The three questionnaires from LBLS46 were merged and processed for missing values. Kmeans was then used for cluster analysis, resulting in 16 clusters. Subsequently, one individual from each cluster was selected for ChatGPT to determine their MBTI personality type, assigning each of the 16 clusters to a specific MBTI personality type. ChatGPT then provided appropriate learning recommendations based on students' personality types and learning motivations. Lastly, recommendations were made for each student regarding potential study partners. The experiment is currently completed up to the step of providing recommendations.

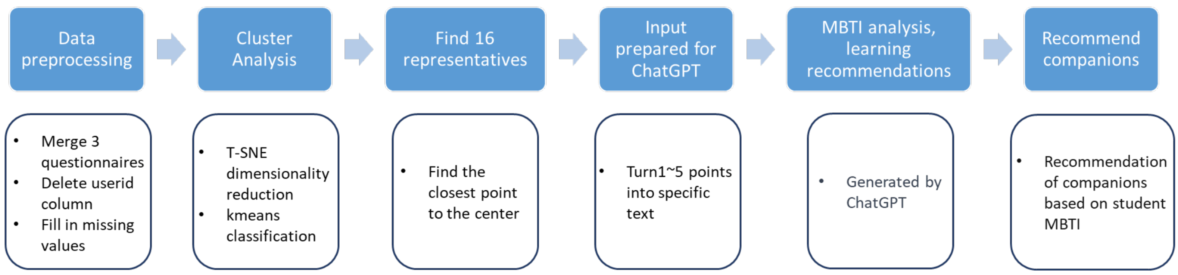

Figure 1: Experimental Process Flowchart

2.3 Data preprocessing, Cluster Analysis and Finding representatives

First, the three sets of data were compared, and userids that appeared in all three questionnaires were selected for merging, resulting in a combined dataset of 205 rows representing 205 students for this method. The userid column was then removed, and missing values were filled with the median. Next, T-SNE was employed for dimensionality reduction. The reason for not using PCA for dimensionality reduction is that PCA performs poorly on nonlinear data compared to T-SNE. Moreover, T-SNE better distinguishes different categories of points under visualization conditions and captures similarities more effectively. After dimensionality reduction, Kmeans clustering analysis was conducted. Table 1 depicts the individual counts of the 16 clusters. Eventually, within each of these 16 clusters, the userids closest to the centroids were singled out, enabling subsequent determination of which MBTI personality type each category belonged to, and the selection of userids closest to the centroids within the 16 categories.

Table 1

The results of the Kmeans analysis and the selection of data points closest to the centroids

Cluster	Count	Representatives_userid
1	11	43f0e2e3fc7691c51613758e2b65928e
2	16	b2649fdf2e1a530529735f6a297d2323
3	16	92f1d409e9283fc62ebc7d59279f15c3
4	15	9fed5a0822e7674f8ebd0fd47c0951da
5	14	b67f08ea9b9e7e9911e15144f038bd3d
6	12	cd1233f691e24539ff101a0cc62d7616

7	13	50833fc4f0545d915ee06bed8670743e
8	12	12b9eba1adfb80bb4900d0f664d64729
9	11	97ff350207ca6a952e2b62129e0549f0
10	11	5b6ff8974f7849c3295a0e4b40f544ab
11	13	2ce542d10444443251e44a3a6dec6eb4
12	13	b64ce7758b9f7e58f1ad8bbcf7811e7d
13	12	6c7ea17b19edee01e39075dfbd783085
14	10	d2cbecf98ecf5cedc5bc4a7424a9b45b
15	15	a5b8d98aa354c067a53ec0d55a2ae574
16	10	3e5fd8ec3f352d90ff3906ae403ebeac

2.4 Converting Questionnaire Data into Text Data

After conducting experiments, it was found that directly presenting questionnaire content and answers ranging from 1 to 5 to ChatGPT for determining the MBTI personality type was unsuccessful. Hence, this study initially processed the extracted questionnaires from the 16 userids. If a student's response was a 5, the word 'definitely' was added to the original question; for a 4, 'sometimes'; 3 was supplemented with 'occasionally'; 2 with 'rarely', and 1 with 'don't'. Table 2 represents the original dataset issues in LBLS467 and the results after conversion.
The conversion method involves three types.
Type 1: In questions srl_s_20 and s_32, specific terms are to be inserted after the two occurrences of the word "I" in the questions.
[1] Type 2 : If the question commenced with 'When', 'If', 'Before', essentially, when these
[2]words appeared at the beginning of the sentence, the specific terms were
[3]inserted after the second 'I'.
Type 3 : For all other remaining questions, the terms were inserted after the first 'I'.

Table 2
Converting questionnaires and answers to generate affirmative sentence descriptions

Question	Type	Converted Questions
s_32 : I plan my schedule so I will have enough time to study programming.	1	I definitely/sometimes/occasionally/rarely/don’t plan my schedule so I definitely/sometimes/occasionally/rarely/ don’t will have enough time to study programming.
srl_m_29 : When I take tests I think of the consequences of failing.	2	When I take tests I definitely/sometimes/occasionally/ rarely/don’t think of the consequences of failing.
srl_s_35 : I have a regular place set aside for studying.	3	I definitely/sometimes/occasionally/rarely/don’t have a regular place set aside for studying.

2.5 Study Suggestions

Finally, the organized .txt file was handed over to ChatGPT to determine the belongingness to one of the 16 MBTI personalities. Initially, we ensured ChatGPT's familiarity with MBTI and its recognition levels for each personality type. Then, I requested ChatGPT to assess the .txt file. Due to the current file transfer limitations of ChatGPT 4, I split the process into two requests for ChatGPT's evaluation. And the results were consolidated. Figures 2 and 3 display the provided prompts given to ChatGPT and its corresponding responses.

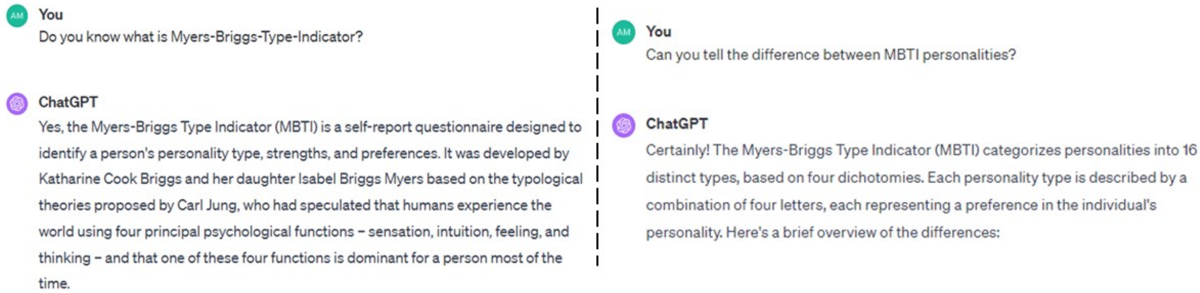

Figure 2 : Ascertaining ChatGPT's familiarity with MBTI and its ability to accurately distinguish between the 16 personality types

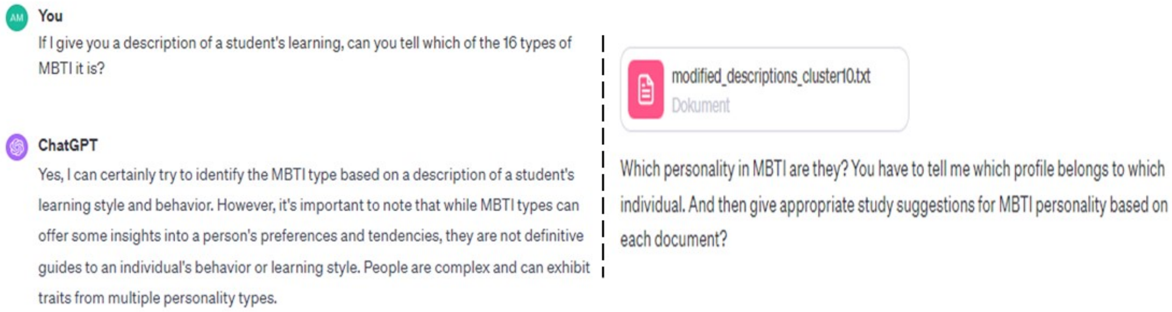

Figure 3 : Verifying with ChatGPT its capability to assess student personalities based on text descriptions before proceeding to request evaluations for 10 .txt files

3. Result

Figure 4 displays the results of sending the 16 .txt files to ChatGPT for analysis to determine the associated MBTI personality type. Subsequently, based on each student's proficiency level, learning habits, and personality traits, appropriate learning recommendations were provided. It is evident that ChatGPT can accurately offer suitable student advice based on their individual traits and personalities.

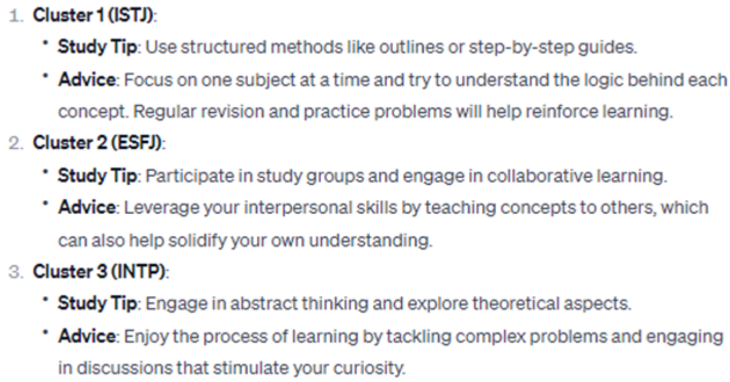

Figure 4 : Results provided by ChatGPT

4. Conclusion

This study focuses on analyzing student learning questionnaires, making suitable adjustments to the questionnaire content, enabling ChatGPT to assess students' MBTI personalities based on their questionnaire descriptions. Furthermore, recommendations and learning directions are provided accordingly.

The next step involves making ChatGPT's recommendations more personalized and comparing analyzed student personalities for similarity. This will suggest who students can learn together with, promoting group learning and aiding in enhancing student learning motivation.

Furthermore, the study has ultimately resulted in a new student personality model, allowing for further exploration in subsequent studies. This enables additional investigations based on students' personality traits, such as developing personalized learning beneficial to students. Teachers can provide differentiated instruction accordingly. Additionally, it contributes to students' mental well-being by offering psychological support and guidance. Moreover, it can guide future career choices based on students' characteristics.

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