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Nudge Messages for E-Learning Engagement and Student's Personality Traits: Effects and Implication for Personalization

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Abstract: The educational use of nudges has received much attention. However, individually optimized nudge interventions have not been well studied. In order to determine which nudge messages are effective for learners with what profiles based on personality inventories, we examined two nudge message interventions that promote the use of learning systems during the summer vacation period to see if they promote use. During summer vacation, students were divided into two groups and sent different types of nudges to each. One is a deadline notification: a notification with the number of days remaining in the summer vacation, and the other is a peer notification: a notification of other students' achievements. We analyzed the frequency of each student's reaction to the notification based on their personality traits. The results show that there was a significant negative correlation between frequency of response to peer notifications and conscientiousness (R=-0.43), and a slight positive correlation between frequency of response to deadline notifications and conscientiousness (R=0.32), peer notifications and neuroticism (R=-0.35) and peer notifications and openness to experience (R=-0.31). These results suggest the possibility of individually optimized nudge interventions by personality.

Keywords: Nudge, message intervention, Big Five Inventory, educational data mining, learning analytics

1. Introduction

The educational use of nudges has received much attention (Damgaard & Nielsen, 2018). The introduction of nudges in education studies is called a framing intervention, which involves deadline-type nudges and peer-type ones (Damgaard & Nielsen, 2018). Some studies using nudge interventions insist on the improvement of students' performance (O'connell & Lang, 2018; Motz, Mallon, & Quick, 2020). However, there are no mentions of peer evaluations while there are of deadline ones. In order to determine which nudge messages are effective for learners with what profiles, we examined two nudge message interventions that promote the use of learning systems during the summer vacation period to see if they are effective. Big Five Inventories have been studied (John, Donahue, & Kentle, 1991), and it is now one of the most popular methods for estimating people's personalities. This study examines the relationship between individual personality and nudge message content according to Big Five Inventories. In particular, we try to answer the following research question:

RQ: To what extent do different types of nudge messages affect students' engagement based on personality type?

2. Related Works

Nudge is a behavioral economics term, and the purpose of its policy is stated as "alter[ing] people's behaviors in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2008). In education studies, the use of nudges has received much attention. A study suggested that students do not mind receiving nudges more often if they perceive the nudges to be useful to them. (Gatare et al., 2021).

The introduction of nudges in education studies is called a framing intervention. Even small changes in the framing of information have the potential to alter behavior and eliminate biases due to cognitive and attentional limitations (Damgaard & Nielsen, 2018). One type of framing intervention is the deadline type. Examples of deadlines are tests and examinations, which are naturally created deadlines, and the more these are, the better students perform (O'Donoghue & Rabin, 1999). Another type of nudge is peer group manipulation, which seeks to facilitate peer-to-peer work. It can be useful in enhancing a sense of social belonging, compelling the creation of social norms for striving, and improving and acquiring skills through partnerships. (Carrell, Sacerdote, & West, 2013; Rogers & Feller, 2016; Papay, Taylor, Tyler, & Laski, 2020).

Zavaleta-Bernuy et al. (2022) showed that reminder messages are useful for some students to complete their homework by its deadline. A study with a closer examination of time periods and durations revealed two distinct patterns that could explain observed increases and found the possibility that low-cost behavioral interventions could be implemented to improve student performance. (O'connell & Lang, 2018). That is, those who received reminders engaged in studying slightly longer on weekends and started that about a few hours earlier on weekdays. Another study showed that assignment submission rates improved with automated nudge reminders by the time rather than supervisors sending out notifications all at once (Motz et al., 2020).

However, individually optimized nudge interventions have not been well studied, and there is no mention of peer evaluations while there are deadline ones. We suppose there could be some variety of nudge messages that take into account the student's personality, and different nudges affect differently on students' quiz-tackling efforts. This study focused on the relationship between individual personality and the content of notifications to determine what types of nudge message interventions would be effective for individuals with these personalities.

A common way to measure personalities is personality inventories. They are a set of questionnaires designed to reveal the personality of a subject in psychology. Big Five Inventory (John et al., 1991) is a well-known method for revealing people's personalities, which is the inventory for classifying people's personalities into five categories: Openness to experience, Extraversion, Agreeableness, Conscientiousness, and Neuroticism, hereinafter referred to as O, A, C, E, N. This taxonomy is a method that has gained a lot of popularity, and there are examples of research on the assignment of appropriate adjectives to these five categories (Hofstee & Raad, 1992; Johnson & Ostendorf, 1993; Goldberg, 1992). In this research, we use the Big Five Inventory to decide each student's personality.

3. Methodology

3.1 Participants and dataset

We conducted the study at a high school in Japan. The study population consisted of 167 students in four classes of first-year high school students. In this experiment, 84 participants from two classes were assigned to Group 1, and 83 participants from two classes were assigned to Group 2.

To estimate students' personalities we used a Japanese version of a questionnaire survey about their personal traits (Murakami, & Murakami, 1997) to measure each of them on a 12-point scale for O, A, C, E, and N respectively (John et al., 1991). The Big Five exam consists of 70 questions, 60 of which are in the form of applicable/not-applicable questions related to one of the five personalities. Students answer these questions with yes or no. Using the student's answers, the score of each personality of each student is calculated by taking the sum of each item.

We collected the data during the summer vacation over the period of July 20 - August 22, 2021. In this period, the students should work on 54 or 58 math quizzes as their homework using a recommender system which is called the explainable recommender system (AI recommender system) (Takami, Dai, Flanagan, & Ogata, 2021, 2022). The system can recommend appropriate questions to students in an explainable way based on their learning logs. They use a learning platform system called moodle (Dougiamas & Taylor, 2002), from which they enter an eBook system called BookRoll (Ogata et al., 2015) to work on assignments. When they log in to Moodle, they are presented with a screen of notifications that they have received, as shown in Figure 1. The students use the BookRoll eBook system to work on their math assignments. It collects learning log data within the LEAF Learning Analytics framework (Flanagan & Ogata, 2018). Every three days (except between Jul. 24 and Jul. 26) at around 22:00, the system sent notifications to students who had not logged in an AI recommender system within 3 days. The deadline type notifications were sent to students in Group 1 and peer type notifications to students in Group 2. Table 1 shows the English translation of the notifications sent to students during the summer vacation.

We collected data from a total of 66 students, 36 from Group 1 and 30 from Group 2, who logged into Moodle during the summer vacation, out of a total of 167 students in Group 1 and Group 2 mentioned above. The 66 students made a total of 198 accesses to the AI recommender system and sent a total of 629 notifications to them.

Table 1. *Contents of a deadline/peer type notification*

Type	Content of notification
Deadline	You don't seem to have logged into an AI recommender system in the last 3 days. The 15 days of the summer vacation period have passed. The summer vacation will end in 16 days. Let's proceed with learning more efficiently with the AI recommendation function.
Peer	You don't seem to have logged into an AI recommender system in the last 3 days. In the last 3 days, 29 people in the class logged in and learned 122 quizzes. You have 50 quizzes left. Let's proceed with learning more efficiently with the AI recommendation function.

Figure 1. Screenshots of message notification in Moodle system

3.2 Data preprocess and prediction

For data analysis, we used the LassoCV model (Tibshirani, 2011) from sklearn.linear_model package, a Python package for machine learning (Pedregosa et al., 2011, available at https://scikit-learn.org/stable/modules/linear_model.html). Lasso is a widely used research model in variable selection. Various methods have been proposed (Freijeiro-González, Febrero-Bande, & González-Manteiga, 2022), and it is also used in Big Five analysis (Tanaka, Nihonsugi, Ohtake, & Haruno, 2021). It performs variable selection and regularization that foster accurate prediction and easy comprehension of the created statistical models. LassoCV can also cross-validate multiple parameters and automatically set the most accurate ones (Friedman, Hastie, & Tibshirani, 2010).

Lasso can deal with a large dimensionality of explanatory variables caused by the variable interaction terms, and it estimates the weights of many non-valid explanatory variables to be zero. Therefore, it can be said that a non-zero weight implies a large contribution.

4. Result

4.1 Reaction rate

To test the effectiveness of the notifications, we measured the reaction rate of students to the notifications as the percentage of notifications received by a student for which there are logs that the student worked on the quiz before receiving the next notification. For example, as shown in Figure 2, the user received a total of 7 notifications, three of which (July 24, July 29, and August 16 indicated in blue) were ones with a record of quiz effort in the period immediately following, so reaction rate is 3/7 ~ 0.43. A higher reaction rate indicates that a higher proportion of those students worked on the problem after reading the message, so it can be said that the higher this value is, the more effective the message is.

Figure 3 shows the relationship between reaction rate and the quiz-tackling operation for each type, which consist of the number of logging in the AI recommender system. Table 2 shows the results of the Pearson correlation analysis. As can be seen from the analysis results, there is a positive correlation between reaction rate and the number of operations, each of which is significant. This means that the higher the reaction rate is, the more times the students work on the quizzes. Note that no such person engaged a lot but missed only one message out of one (reaction rate is 0).

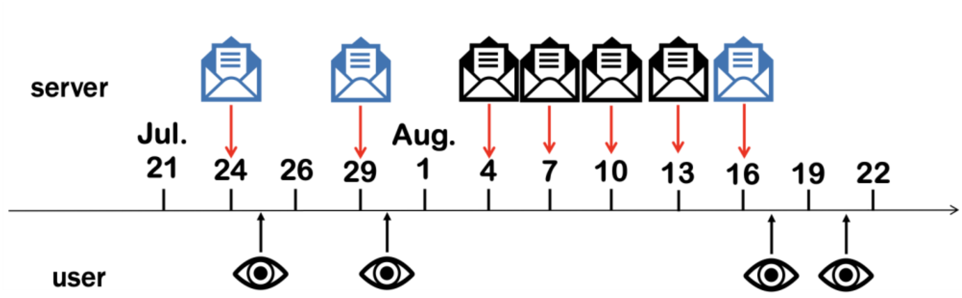

Figure 2. An example of a user's action and the server sending messages

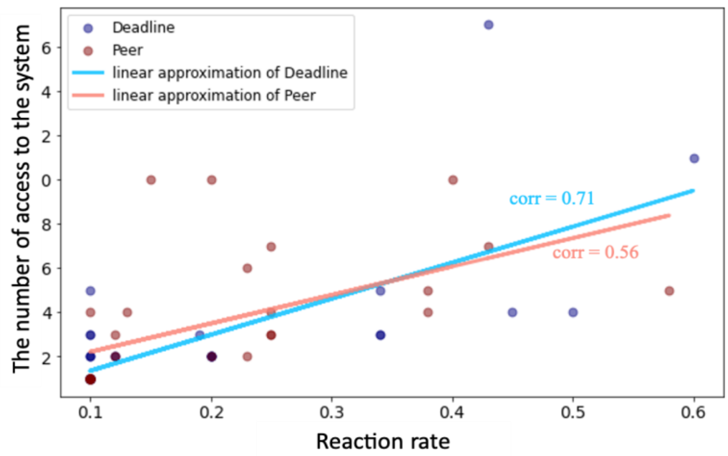

Figure 3. Relationship between the number of access to the system and reaction rate

Table 2. *Correlation analysis between reaction rate and the number of access to the system*

Message type	Pearson correlation coefficient	*p-value*
Deadline	0.71	< 0.001***
Peer	0.56	0.0013***

*** $p < 0.01$

4.2 Relationship between personal traits and reaction rate

We used LassoCV, which was a well-used analysis of personality traits (Tanaka et al., 2021) to find out which personality traits were significantly correlated with the reaction rate. We used 20% of the data as test data and trained using 5-fold cross-validation. We used grid search to determine the optimal regularization parameter α in the range $10^{-6} \leq \alpha \leq 10^{2}$.

Table 3 shows the standardized coefficient values for each personality trait and the optimal α, and Figure 4 visualizes the results of standardized coefficients. As a result, we found that there is a tendency for a positive correlation with C for the deadline type, and a negative correlation with O, C, and N for the peer type. There is a slight negative correlation with E for the peer type.

Table 3. *Obtained values using Lasso*

Notification Type	Standardized coefficients					α
	O	A	C	E	N	
Deadline	0	0	0.0173	0	0	0.0251
Peer	–0.0212	0	–0.0412	–0.0026	–0.0362	0.0100

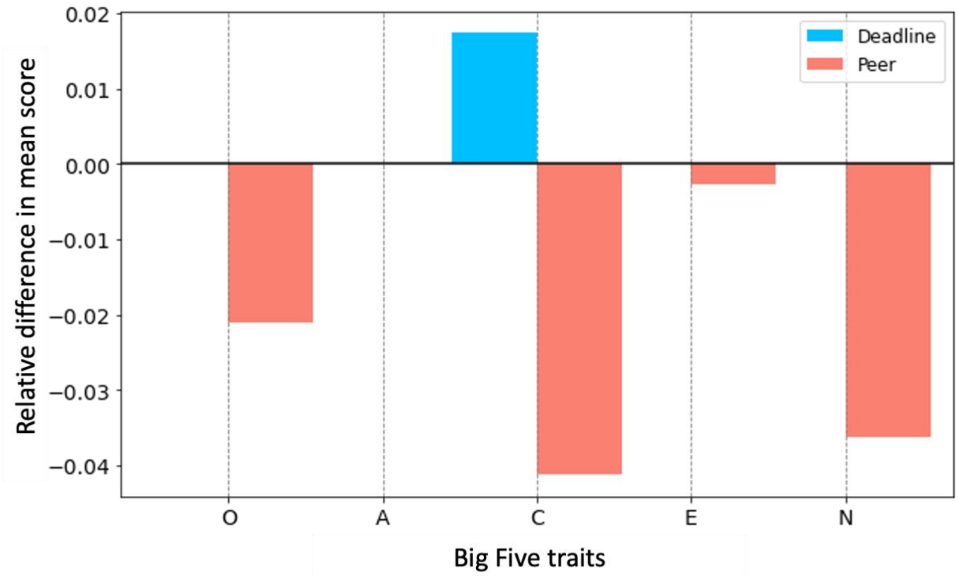

Figure 4. Standardized coefficients obtained using lasso

Table 4 shows the correlation coefficients and p-values for the relation between the reaction rate and the C score in the deadline type or the C, O, N or E score in the peer type, which has a non-zero relative difference in Lasso analysis. Figure 5 shows the relationship between the reaction rate and the C score, and Figure 6 shows the relationship between the reaction rate and the O, N or E score. For visualization using box plots with respect to the personal traits scores, the 33rd, and 66th percentiles were used to classify the respondents into three groups, with Low, Middle, and High in descending order from lowest to highest scores.

There was a significant negative correlation between the C score and reaction rate for peer notifications. This result suggests that the lower the C score, the more susceptible to peer notifications.

For the other relationship, there were significant tendencies in correlations. What these suggest is as follows: the higher the C score, the more susceptible to deadline notifications, and the lower the O or N score, the more susceptible to peer notifications. There is no significant correlation between E score and reaction rate for peer notifications.

According to previous research on personal traits using the Big Five, adjectives used to describe people with a tendency toward conscientiousness include "punctual" (Johnson & Ostendorf, 1993) or "systematic" (Hofstee & Raad, 1992). From these studies, it can be concluded that sending notifications to students with a tendency toward conscientiousness can be effective for reasons such as time or school systems. On the other hand, people with low conscientiousness, described by words such as "careless" (Johnson & Ostendorf, 1993), are generally more likely to implement a problem without examining it closely, so nudges that notice peer engagement are good for their study planning. Therefore, notifications that others were working on the problem are considered to be effective. People with low values of "openness to experience" are described by words such as "unreflective" (Goldberg, 1992), so it can be considered that knowing how others are tackling a problem could give them an opportunity to study that they were not aware of themselves. People with low values of neuroticism are described by words such as "envious" or "emotional" (Goldberg, 1992), so they are considered to be more susceptible to notifications that tell them how others are dealing with quizzes. Table 4. *Correlation analysis between various traits and reaction rate*

Type	Personal traits	Correlation coefficient	*p-value*
Peer	C	–0.43	0.0173 **
Deadline	C	0.32	0.0585 *
Peer	O	–0.35	0.0602 *
Peer	N	–0.31	0.0910 *
Peer	E	–0.26	0.1711

** $p < 0.05$, * $p < 0.1$

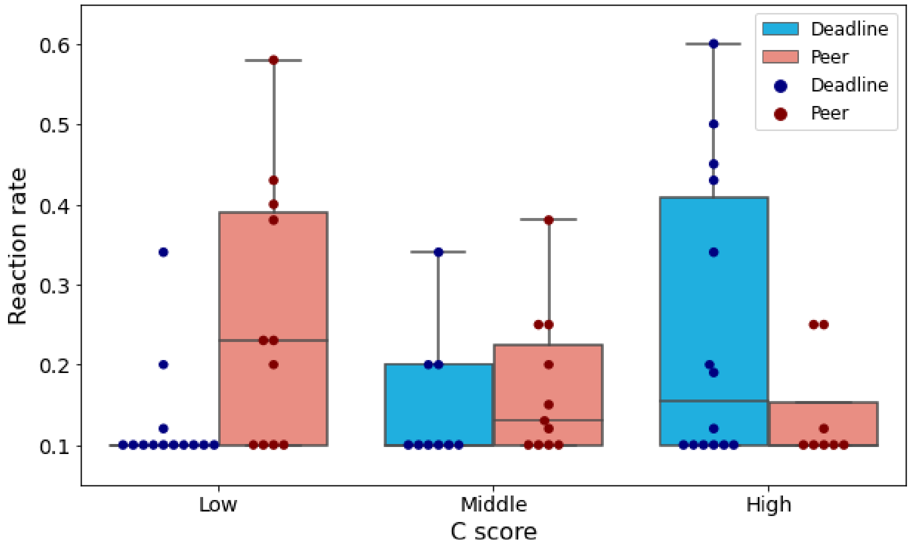

Figure 5. Relationship between reaction rate and C score for both types of notification

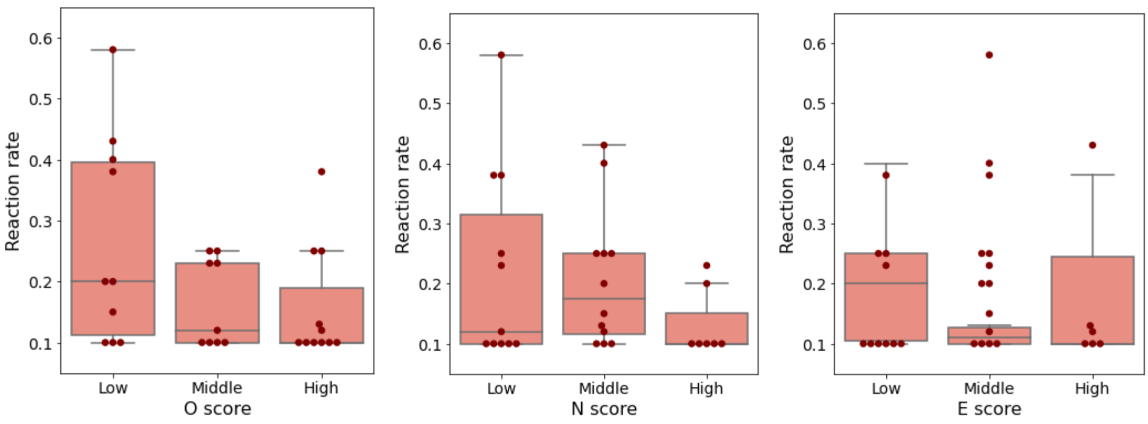

Figure 6. Relationship between reaction rate and O, N, or E score for peer notification

5. Limitations and future research

There are some limitations to this study. First, this study is not a study of individually optimized interventions, but we showed that different nudge messages had different effects on different personalities, which is a key finding of individually optimized interventions based on personality traits. For future research, it is necessary to develop a system that automatically optimizes and sends messages with individually optimized nudges based on personalities and verifies whether it is actually more effective than existing ones. There is also room to examine the effects of various other nudges (Damgaard & Nielsen, 2018) on their personalities, such as goal setting (Goal setting nudge) whereby students set their own goals and nudges that work on students' parents. Furthermore, it remains to be investigated whether nudge messages can improve the degree to which students do their regular homework during the semester, not during the summer vacation. Another limitation of the Big Five Inventory, asking students nearly 70 questions about the Big Five Inventory to K-12 students would be burdensome and needs to be a way to reduce the burden of conducting them such as predicting personality traits from the learning logs (Takami, 2022).

6. Conclusion

In this study, we tested what message content would have an effect on students of any personality. First, we divided the subject students into two groups, sending deadline-type notifications to one group and peer-type notifications to the other. Next, using Lasso regression, we determined which personalities correlated with the effectiveness of the notifications. Finally, for each of the personalities that seemed to correlate with effectiveness, we examined the correlation with the response rate of the notification. The results show that there was a significant negative correlation between frequency of response to notifications and conscientiousness for peer notifications (R=-0.43), a slight positive correlation between frequency of response to notifications and conscientiousness for deadline notifications (R=0.32), neuroticism for peer notifications (R=-0.35) and openness to experience for peer notifications (R=-0.31). These results suggest the possibility of individually optimized nudge interventions altering learners' behaviors by personality.

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