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Matching Intervention Messages Considering Complex Personality Types of High School Students

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Abstract: In this paper, we proposed intervention messages that consider the complexity of student personalities. Because of the increasing importance of individually optimized learning, the intervention for the student is also desired to be tailored. While previous studies have found the appropriate message content related to one or several personality traits, no study has been conducted to send individually optimized messages with consideration of each student's complex personality traits. In this study, we conducted the clustering of students based on Big Five test scores and then determined the nature of each cluster and the type of intervention message related to that nature. According to the clustering analysis, the students were categorized into three groups. Considering the personality trait of these groups, we decided tailored messages for each group.

Keywords: Message intervention, big five inventory, individually optimized learning, personality, classification

1. Introduction

The use of the flaming intervention is the introduction of nudges in educational studies (Damgaard & Nielsen, 2018), and it can be an effective way of individually optimized message intervention. Some studies using nudge interventions insist on the improvement of students' performance (Motz et al., 2020; O'connell & Lang, 2018). While previous studies show that flaming intervention can be applied to individually optimized message intervention (Wall et al., 2019; Yamauchi et al., 2022) using Big Five Inventory (John et al., 1991), these studies focus on only one or several types of personality traits, and they did not propose the specific message type for each cluster.

Hence, the aim of our research is to suggest an approach for identifying effective intervention messages considering students' complex personality traits. We try to investigate the following research question: *what are the clusters of complex personality types of high school students and what is the optimized message for each of those clusters?*

2. Literature Review

2.1 Big Five Inventory

Personality inventories are a common approach for evaluating personalities in psychology. They involve a series of questionnaires designed to uncover a subject's personality. One well-known inventory is the Big Five Inventory (John et al., 1991), which categorizes personalities into five groups. This method is highly popular, and researchers have even developed lists of appropriate adjectives for each category (Goldberg, 1992; Hofstee &

Raad, 1992; Johnson & Ostendorf, 1993). The relationships between each Big Five trait and adjectives are represented in the following items, where (+) means the profile those who have the high Big Five score are likely to have, and (-) means the ones those who have the low Big Five score are likely to have:

- Openness to experience: inventive (+), curious (+), consistent (-), cautious (-)
- Extraversion: active (+), talkative (+), shy (-), quiet (-)
- Agreeableness: kind (+), cooperative (+), selfish (-), cold (-)
- Conscientiousness: responsible (+), organized (+), extravagant (-), careless (-)
- Neuroticism: anxious (+), angry (+), calm (-), unemotional (-)

In our research, we will use the Japanese Big Five Inventory to determine each student's personality.

2.2 Message Interventions in Educational Context

In education studies, the use of nudges has received much attention (Damgaard & Nielsen, 2018). Nudge is defined as "alter[ing] people's behaviors in a predictable way without forbidding any options or significantly changing their economic incentives", which is the term of economics (Thaler & Sunstein, 2008). 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). In this study, we try to use flaming intervention for an individually optimized system.

It is possible to create various types of nudges that consider the student's personality, which may have varying impacts on how students approach their quizzes. One study determined on an individual basis which messages are most appropriate based on profile characteristics (Yamauchi et al., 2022). According to this study, there existed a noteworthy inverse association between the rate of responding to notifications and conscientiousness for peer notifications. Additionally, there was little favorable correlation between the frequency of notification responses and conscientiousness for deadline notifications. Moreover, neuroticism was correlated with peer notifications, while openness to experience was correlated with peer notifications as well.

Although some researches show the effectiveness of intervention related to one type of or several types of personality (Wall et al., 2019; Yamauchi et al., 2022), no study shows the application of individually optimized content message considering each student's all complex personality. It is difficult to decide what type of message should be sent to each student because every student has a complex personality. In this study, we challenged the clustering of the students in terms of their personality and made a decision of sending what type of message and then apply it to students.

3. Research Design

This study was conducted in a high school in Japan. 279 1st-grade students (15-16 years old) participated in this experiment. To estimate students' personalities, we used a Japanese version of a questionnaire survey which consists of 60 questions about their personal traits (Murakami & Murakami, 1997). This can be helpful when someone takes the survey to those who cannot understand the original English questionnaire. The Big Five assessment comprises 70 questions, out of which 60 are presented as true/false questions relating to one of the five personality traits. Each student's personality score is determined by adding up the scores for each item on a 12-point scale by the student's answers. We collected Big Five personality data from 120 students of all 279 in this experiment.

We designed and developed a message-sending system called "LRS2Message", which combines Learning Record Store (LRS), Learning Management System (LMS), and Analysis Tool. Figure 1 describes the chart of to whom the system sends a message and how to send messages to the environment. We schedule the message token to store the message logs into LRS by pushing the checkboxes and a specific button in Analysis Tool (surrounded by a red square in Figure 1). On the other hand, we used LRS2Message to set some emails with sending contents, timings, and dates. Once the time has come, LRS2Message gives LRS the query to decide to whom the system sends a scheduled message. LRS2Message also gets the result of the query, and then it sends a message to LMS according to the result of the query. We can also send a message manually with Analysis Tool, so we used it to send a part of the message.

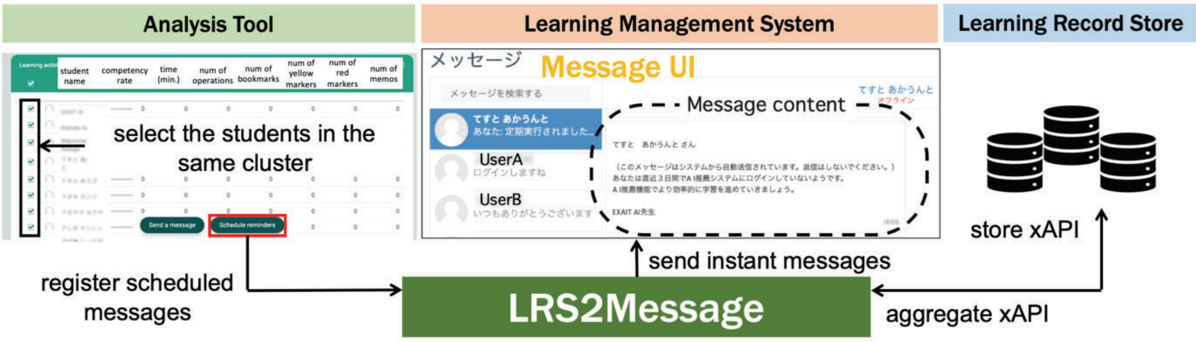

Figure 1. Message-sending flow using LRS2Message

Because of the many variables of personality traits, we can't easily decide with some comprehensive rules what type of contents of messages the student receives. Therefore, we conducted the clustering with Big Five test scores of five personality traits as explanatory variables and then we decided the proper message contents of each cluster instead of making rules that can assign property to each student. Based on the result of the k-means elbow plot of that clustering, we found that 3 clusters seem the best number of clusters because it is the point at which the absolute value of the change in slope is greatest. Previous studies follow this result that we can classify the students into 3 clusters (Asendorpf & van Aken, 2001, 1999; Robins et al., 1996; Takami et al., 2023; Wall et al., 2019).

4. Findings

Based on the result of the elbow plot, we clustered 120 students into three clusters. Table 1 shows the cluster name, the number of people in the cluster, the score means and SD of students' personality traits of each cluster, and the graphs of the distribution of students' personality traits. According to these results, we named these clusters whose names represent the property of each cluster. The first cluster has a **hi**gher-than-average score for all **five** personality traits, so we named this cluster "Hi5". The second cluster has a higher-than-average score for **a**greeableness and **e**xtraversion and a lower-than-average score for **n**euroticism. We named this cluster "AEn" based on the characteristic score. The third cluster has a higher-than-average **n**euroticism score and has lower than average **o**penness to experience or **e**xtraversion score. According to the features, we finally named the cluster "Noe". We also found from ANOVA analysis of the data that all of the Big Five personality scores of one specific cluster are significantly different from the other ones. This result fastens the validity of the assignment of the properties of each cluster.

At the second step, we assigned which message to send to each group of the cluster. Students in the Hi5 group have the highest average C score of the three clusters. One previous research shows that it is better for students' engagement to send deadline-type message to people who have a high C score (Yamauchi et al., 2022). Thus, we think it is best to send a deadline-type messages to them. Students in the Noe group have the lowest average C score of the three clusters. One study also shows that it is better for students' engagement to send peer-type messages to people who have a low C score (Yamauchi et al., 2022). Thus, we concluded that it is best to send peer-type messages to them. Students in the AEn group have the lowest N score of all three groups. Students who have a low N score are unemotional

(Hofstee and Raad, 1992) and calm (Johnson & Ostendorf, 1993). Thus, we decided to send messages which have the content on prior actions of herself/himself.

Considering the personality trait of each message type, we decided what contents of the message are the best to send in this engagement context. The following sentences are examples of the content:

- Deadline: “You have not worked on the recommendation system or test set maker in the last 3 days. The exam will begin on February 24. The exam date is only 11 days away. AI recommendation will help you learn more efficiently.”
- Peer: “You have not worked on the recommendation system or test set maker in the last 3 days. During the period, the recommendation system or test set maker was used by 7 people, and 15 exercises were solved. AI recommendation will help you learn more efficiently.”
- Commitment: “You have not worked on the recommendation system or test set maker in the last 3 days. You have solved one recommendation exercise so far. You need to solve 4 more exercises to use Test Set Maker and further improve your academic performance. AI recommendation will help you learn more efficiently.”

Table 1. *Classification property*

Type	Mean (SD) Score of each personality trait				
(# of people)	C	N	O	A	E
Hi5 (48)	5.98 (2.92)	9.46 (1.89)	6.52 (2.48)	7.96 (2.14)	8.15 (2.47)
Noe (31)	3.27 (2.72)	9.76 (2.15)	2.12 (2.01)	6.27 (3.33)	2.22 (2.41)
AEn (41)	4.68 (2.71)	2.58 (1.84)	4.26 (3.46)	8.45 (1.84)	8.00 (3.32)

5. Discussion and Limitations

In order to provide appropriate message interventions that take into account complex personalities, clustering was performed on the students and the characteristics of each cluster were looked at to determine appropriate intervention messages. The results showed that the best approach was to divide the students into three clusters, and we also found that the appropriate intervention message type for each is “Deadline,” “Peer,” or “Commitment” based on previous literature (Wall et al., 2019; Yamauchi et al., 2022). Following notes are the features of each cluster:

Group “Hi5”: This group has a higher C score than the others, and previous study shows people with higher C score tends to be punctual (Back et al., 2006). One study has shown that the more deadlines there are, the better students tend to perform (Rabin & O’Donoghue, 1999). From that point of view, Hi5 students can be susceptible to a deadline-type message.

Group “Noe”: The other group has a higher N score and lower E score than that of the others, and previous study shows that people with this personality are obeying those in authority, and they fear social disapprovement (Wall et al., 2019). Previous studies (Carrell et al., 2013; Papay et al., 2020; Rogers & Feller, 2016) have shown that intervention which encourages peer-to-peer collaboration can be effective in promoting a sense of social belonging, establishing social norms for striving, and improving skills through partnerships.

Group “AEn”: This group has a higher A score and a lower N score than that of the others, and previous studies showed that people with a higher A score and a lower N score are likely to maintain consistent beliefs they are owning (Cialdini, 2001; Wall et al., 2019). They are more susceptible to commitment persuasion strategy. Those who have strong social skills are more likely to be influenced to perform a behavior if it aligns with their existing beliefs or prior actions (Cialdini, 2001; Wall et al., 2019). Thus, we selected to send a commitment-type message to them.

One limitation of the experimental result is that it is not necessarily true that everyone can adapt the cluster's rule. For example, we can see from Table 1 that there is a student who has a 1-point C score even in Hi5. For the solution of these problems, we could use more indicators to evaluate students' personality like Dark Triad Traits (Jonason & Webster, 2010) or Type-D (Denollet, 2005).

6. Conclusion and Future Works

In this paper, we suggested intervention messages considering each student's complex personality and presented techniques for visualizing the outcomes using relevant indicators extracted. First, student personalities were investigated using the Big Five test, and then students were clustered using it. The clustering results and previous papers were then consulted to determine the nature of each cluster and the type of intervention message adapted to that nature. The clustering results showed that the students were divided into three groups, and we concluded that the best messages for each of these groups were "Deadline," "Peer," and "Commitment", respectively. Previous works of literature follow the results of this clustering and the validity of the appropriate intervention messages.

We also conducted an intervention experiment with the same cohort of students to understand the effects of matched and random messaging. However, due to the small number of student engagement logs, the result is not conclusive and would require further study.

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References

Asendorpf, J. B., Borkenau, P., Ostendorf, F., & Van Aken, M. A. G. (2001). Carving personality description at its joints: Confirmation of three replicable personality prototypes for both children and adults. *European Journal of Personality, 15*(3), 169-198.

Asendorpf, J. B., & van Aken, M. A. G. (1999). Resilient, overcontrolled, and decontrolled personality prototypes in childhood: Replicability, predictive power, and the trait-type issue. *Journal of Personality and Social Psychology, 77*(4), 815-832.

Back, M. D., Schmukle, S. C., & Egloff, B. (2006). Who is late and who is early? Big five personality factors and punctuality in attending psychological experiments. *Journal of Research in Personality, 40*(5), 841-848.

Carrell, S. E., Sacerdote, B. I., & West, J. E. (2013). From natural variation to optimal policy? The importance of endogenous peer group formation. *Econometrica, 81*(3), 855-882.

Cialdini, R. B. (2001). The science of persuasion. *Scientific American*, *284*(2), 76-81.

Damgaard, M. T., & Nielsen, H. S. (2018). Nudging in education. *Economics of Education Review, 64*, 313-342.

Denollet, J. (2005). DS14: Standard assessment of negative affectivity, social inhibition, and Type D personality. *Psychosomatic medicine, 67*(1), 89-97.

Goldberg, L.R. (1992). The development of markers for the big-five factor structure. *Psychological Assessment, 4*(1), 26-42.

Hofstee, W. K. B., & Raad, B. D. (1992). Integration of the big five and circumplex approaches to trait structure. *Journal of Personality and Social Psychology, 63*(1), 146-163.

John, O. P., Donahue, E. M., & Kentle, R. L. (1991). Big five inventory. *Journal of Personality and Social Psychology*.

Johnson, J. A., & Ostendorf, F. (1993). Clarification of the five-factor model with the abridged big five dimensional circumplex. *Journal of Personality and Social Psychology, 65*(3), 563-576.

Jonason, P. K., & Webster, G. D. (2010). The dirty dozen: A concise measure of the dark triad. *Psychological assessment, 22*(2), 420-432.

Motz, B. A., Mallon, M. G., Quick, J. D. (2020). Automated educative nudges to reduce missed assignments in college. *IEEE Transactions on Learning Technologies, 14*(2), 189-200.

Murakami, Y., & Murakami, C. (1997). Scale construction of a "Big Five" personality inventory. *The Japanese Journal of Personality, 6*(1), 29-39.

O'Connell., S. D., & Lang, G. (2018). Can personalized nudges improve learning in hybrid classes? Experimental evidence from an introductory undergraduate course. *Journal of Research on Technology in Education, 50*(2), 105-119.

Rabin, M., & O'Donoghue, T. (1999). Doing it now or later. *American Economic Review*, *89*(1), 103-124.

Papay, J. P., Taylor, E. S., Tyler, J. H., & Laski, M. E. (2020). Learning job skills from colleagues at work: Evidence from a field experiment using teacher performance data. *American Economic Journal: Economic Policy*, *12*(1), 359-388.

Robins, R. W., John, O. P., Caspi, A., Moffitt, T. E., & Stouthamer-Loeber, M. (1996). Resilient, overcontrolled, and undercontrolled boys: Three replicable personality types. *Journal of Personality and Social psychology*, *70*(1), 157.

Rogers, T., & Feller, A. (2016). Discouraged by peer excellence: Exposure to exemplary peer performance causes quitting. *Psychological science*, *27*(3), 365-374.

Takami, K., Flanagan, B., Dai, Y., & Ogata, H. (2023). Toward trustworthy explainable recommendation: Personality based tailored explanation for improving e-learning engagements and motivation to learn. *Proceedings 13th International Conference on Learning Analytics & Knowledge.*

Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. *Const Polit Econ, 19*, 356-360.

Wall, H. J., Campbell, C. C., Kaye, L. K., Levy, A., & Bhullar, N. (2019). Personality profiles and persuasion: an exploratory study investigating the role of the Big-5, Type D personality and the Dark Triad on susceptibility to persuasion. *Personality and Individual Differences, 139*, 69-76.

Yamauchi, T., Takami, K., Flanagan, B., & Ogata, H. (2022). Nudge messages for e-learning engagement and student's personality traits: Effects and implication for personalization. *Proceedings of 30th International Conference on Computers in Education, 2*, 42-50.