Kashihara, A. et al. (Eds.) (2024). Proceedings of the 32nd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Exploring the Relationship of Personality Domains and Visual Attention Patterns in Novice Programmers

Caren PACOL[ab*], Maria Mercedes RODRIGO[a] & Christine Lourrine TABLATIN[b]
[a]*Ateneo de Manila University, Philippines*
[b]*Pangasinan State University, Philippines*
*ambat_caren@yahoo.com

Abstract: Researchers have long studied how novice programmers interpret compiler error messages during debugging. This study investigates the link between personalities and visual attention patterns. We measured traits using the Big Five Personality Test (John and Soto, 2017) and eye-tracking data from 63 participants at two Philippine universities. They located bugs in five programs with syntax errors, each 15 to 35 lines long, using constructs from the first 6 to 8 weeks of a programming course. Each program had one syntax error, either literal or non-literal. Participants viewed images of the programs and error messages, marking errors with a custom viewer. We found that students with high agreeableness and conscientiousness showed minimal attention to compiler error messages and error lines, respectively. The lack of correlation between these traits and performance scores makes it uncertain if these students with high agreeableness and high conscientiousness are also high performers. This study suggests educators might develop strategies potentially leveraging agreeableness and conscientiousness, such as collaborative learning. Future work will investigate run time errors, analyze patterns, and create strategies to help novices address them effectively.

Keywords: Debugging, Eye tracking, Novice programmers, Personality Traits

1. Introduction

Debugging is essential in computer science, with compiler error messages playing a crucial role. There's interest in how novice programmers interpret these messages and how personality traits influence their approach.

Eye tracking quantifies visual attention during programming (Chandrika & Amudha, 2017; Barik et al., 2017; Vasconcelos et al., 2020) and reveals how personality affects this process. Conscientious individuals focus systematically, boosting programming performance (Hasanzadeh et al., 2019), while those with maladaptive traits might struggle due to avoidance strategies (Afshar et al., 2015; van Berkel, 2009).

Understanding these dynamics can lead to personalized learning interventions. Combining insights from eye-tracking and personality research allows educators to design programs that address diverse learning needs, improving programmer success.

Research has examined how personality traits influence programming. Karimi et al. (2016) found that Openness, Conscientiousness, Extraversion, and Agreeableness enhance programming performance, while some Openness aspects and Neuroticism hinder it. Dirzyte et al. (2021) reported that Extraversion, Conscientiousness, and reduced Negative Emotionality predict learning motivation factors. Amin et al. (2020) indicated that Openness, Extraversion, and Conscientiousness positively predict creativity, with Neuroticism having a negative impact. Although past work has explored code comprehension and debugging, research on personality traits and visual attention in debugging remains limited. This study aims to explore the relationship between personality traits and visual attention in novice programmers.

This research extends a project on eye tracking and student abilities. Tablatin and Rodrigo (2023) found high-performing students focus more on the buggy lines identified by the compiler error messages. Pacol, Rodrigo, and Tablatin (2024) showed that error type affects visual attention. This study examines how personality traits relate to visual attention patterns. Our research questions include:

1. How does the relationship between novice programmers' visual attention to compiler error messages and their personality domain scores differ between those with high and low scores?
2. How does the relationship between novice programmers' visual attention to error lines and their personality domain scores differ between those with high and low scores?

1.1 Components of the Big Five Personality Domains

Our interest in personality traits comes from research showing their relation to learning success. Studies have found that certain personality domains positively affect academic achievements (Wang et al., 2023; Nechita et al., 2015; Hazrati-Viari et al., 2011). Soto and John (2017) developed and validated the Big Five Inventory-2 (BFI-2), demonstrating it as a reliable and valid measure of personality traits, improving upon the original BFI. Many studies use the Big Five Inventory (BFI) to assess personality traits.

The Big Five personality domains—Extraversion, Agreeableness, Conscientiousness, Negative Emotionality, and Open-Mindedness—describe cognitive, emotional, and behavioral variations (Goldberg, 1993; John et al., 2008; McCrae & Costa, 2008).

Extraversion consists of Sociability, Assertiveness, and Energy Level. It's linked to positive affect and physical activity beyond sociability (De Young et al., 2007; Lucas et al., 2008; Watson & Clark, 1997). Agreeableness includes Compassion, Respectfulness, and Trust—traits concerning others' well-being, treating others well, and trusting positive beliefs (Goldberg, 1999; De Young et al., 2007; McCrae & Costa, 2008). Conscientiousness consists of Organization, Productiveness, and Responsibility, focusing on orderliness, work ethic, and meeting obligations (Soto & John, 2017). Negative Emotionality involves Anxiety, Depression, and Emotional Volatility, differentiating fear, sadness, and anger (Goldberg, 1999; McCrae & Costa, 2008; Saucier & Ostendorf, 1999). Open-mindedness reflects intellectual curiosity, creativity, and openness (Soto & John, 2017). The BFI is a reliable tool for personality assessment (Soto & John, 2017) and was used in our study.

2. Methodology

The study involved 63 college students who had completed at least one programming course: 31 from School A in Metro Manila and 32 from School B in Pangasinan. The final sample size varied due to data exclusions, with specifics discussed later.

Two sets of stimuli were used, each with identical problems. The stimuli, code complexity, and experimental procedure followed those described in Tablatin and Rodrigo (2023). The data sources and data pre-processing steps were the same as those in Tablatin and Rodrigo (2023) and Pacol et al. (2024).

3. Analysis and Results

We analyzed data from 44 students, excluding 12 from School A and 6 from School B due to insufficient fixation recordings or frequent head movements, and one from School B due to incomplete personality test responses. Thus, the final analysis included 19 students from School A and 25 from School B.

The Shapiro-Wilk test showed that for the combined datasets, while personality domain scores were normally distributed, the average proportional fixation count and average proportional fixation duration were not. However, average proportional fixation count and average proportional fixation duration on error lines for high and low personality scores were normally distributed. Meanwhile, the results of the normal distribution tests for the average proportional fixation count and average proportional fixation duration on compiler error messages of participants with high and low personality domain scores are shown in Table 1.

We first conducted an overall analysis using Spearman's rank correlation to assess relationships between visual attention patterns and personality scores. Then, we analyzed interactions between high (+1 *SD*) and low (-1 *SD*) personality scores using Welch's t-tests for normally distributed data and Mann-Whitney U tests for non-normally distributed data to determine significant differences in visual attention patterns.

Table 1. *Results of Normal Distribution Tests on Visual Attention Metrics (Compiler Error Messages)*

	Average Proportional Fixation Count (APFC)		Average Proportional Fixation Duration (APFD)	
Personality Domain	Class	Result	Class	Result
Extraversion	High	Normal	High	Not Normal
Extraversion	Low	Normal	Low	Normal
Agreeableness	High	Normal	High	Normal
Agreeableness	Low	Normal	Low	Not Normal
Conscientiousness	High	Not Normal	High	Not Normal
Conscientiousness	Low	Normal	Low	Not Normal
Negative Emotionality	High	Normal	High	Normal
Negative Emotionality	Low	Not Normal	Low	Not Normal
Open-mindedness	High	Normal	High	Not Normal
Open-mindedness	Low	Normal	Low	Not Normal

3.1 Relationship Between Visual Attention to Compiler Error Messages and Personality Domain Scores in High and Low Scorers

We first conducted Spearman's rank correlation analysis to explore relationships between personality domain scores and visual attention metrics. We found significant moderate negative correlations between Agreeableness scores and both average proportional fixation count (Spearman's r = -0.44, p = 0.003) and average proportional fixation duration (Spearman's r = -0.49, p < 0.01), indicating that as Agreeableness scores increase, both average proportional fixation count and average proportional fixation duration on compiler error messages decrease. No significant correlations were found for other personality domains.

Figures 1and 2 illustrate the statistically significant correlations.

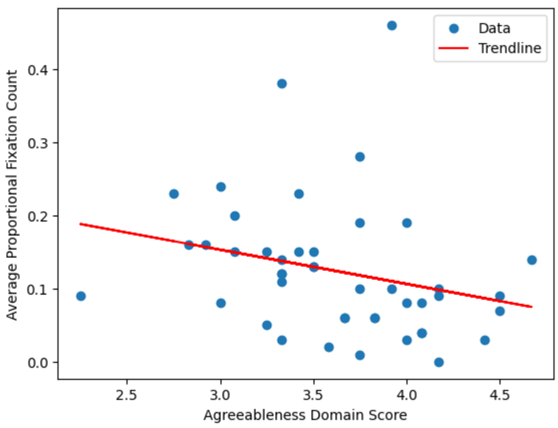

Figure 1. Correlation of Average Proportional Fixation Count with Agreeableness Score

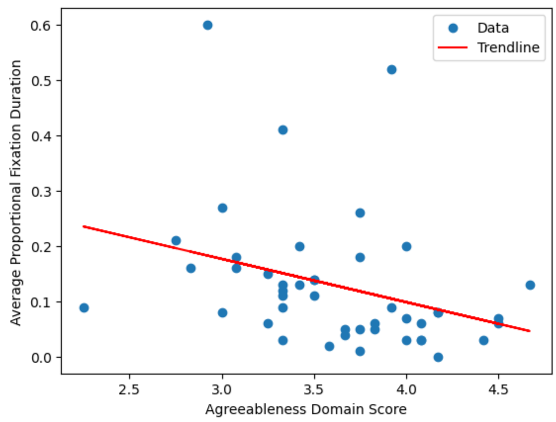

Figure 2. Correlation of Average Proportional Fixation Duration with Agreeableness Score

In School A, we found a moderate negative correlation between Agreeableness scores and average proportional fixation count (Spearman's r = -0.55, $p \approx 0.01$) and average proportional fixation duration (Spearman's r = -0.57, $p \approx 0.01$). No significant correlations were found in School B or for other personality domains.

3.1.1 Difference between Novice Programmers with High and Low Personality Domain Scores' Visual Attention to Compiler Error Messages

We calculated average personality domain scores for Extraversion, Agreeableness, Conscientiousness, Negative Emotionality, and Open-mindedness, and classified participants into high (+1 *SD*) and low (-1 *SD*) score groups. We then compared average proportional fixation count (APFC) and average proportional fixation duration (APFD) on compiler error messages for these groups.

Participants with high Agreeableness scores tend to have a lower APFC on compiler error messages compared to those with low Agreeableness scores. With a Bonferroni-corrected significance level of 0.01, the p-value (< .01) indicates a significant difference in APFC. Similarly, those with high Agreeableness also showed a lower APFD compared to those with low Agreeableness scores, with a p-value (< .01) supporting a significant difference. No significant differences were found for other personality domains.

3.2 Relationship Between Visual Attention to Error Lines and Personality Domain Scores in High and Low Scorers

We examined the correlation between average personality domain scores and average proportional fixation count on error lines. A weak negative correlation with Conscientiousness was found, suggesting that higher Conscientiousness scores might be linked to lower average proportional fixation count, but the p-value of 0.02 exceeds the corrected significance level of 0.01, indicating the result may not be significant after adjustment.

In School A, there was a strong negative correlation between Conscientiousness scores and both average proportional fixation count (Spearman's r = -0.85, $p < 0.01$) and average proportional fixation duration (Spearman's r = -0.81, $p < 0.01$), even after Bonferroni correction. This indicates that higher Conscientiousness scores are associated with significantly lower average proportional fixation count and lower average proportional fixation duration on error lines. No significant correlations were found between eye tracking metrics and other personality domain scores in either school.

3.2.1 Difference between Novice Programmers with High and Low Personality Domain Scores' Visual Attention to Error Lines

We compared the average proportional fixation count and average proportional fixation duration on error lines for participants with high and low scores in Extraversion. Participants with high Extraversion scores had fewer fixations on error lines compared to those with low scores. With a significance level of 0.01 and Bonferroni correction, the p-value (.03) did not indicate a significant difference. No significant differences were found in the average proportional fixation duration on error lines or between high and low scores in other personality domains.

4. Discussion and Conclusion

This study relates personality domains with visual attention in novice programmers. Students with high agreeableness and conscientiousness tend to allocate minimal attention to compiler error messages and error lines, respectively. This seems counterintuitive. We expected highly conscientious students to focus more on error lines, potentially boosting performance. In order to investigate this possibility, we first tried to determine the relationship between these personality traits and performance. Using Spearman's rank correlation due to non-normally distributed data, we found no significant correlations between agreeableness and performance (*r* = 0.198, *p* = 0.197). For conscientiousness and performance, we tested the data from School A only, since it was in this dataset where we found statistically significant correlations between visual attention on error lines and average conscientiousness scores. However, conscientiousness and performance for School A were not significantly correlated either (*r*= -0.218, *p*= 0.370). Therefore, we could not statistically detect a significant relationship between these personality traits and performance.

Literature suggests reasons for the lack of correlation between personality traits and performance. Research indicates that students with different personalities approach code parsing differently. High conscientiousness in novices often leads to a depth-first debugging style, which contrasts with the broader approach of experts (Karimi et al., 2016). Personality effects might also depend on experience or other traits; for example, low agreeableness might excel with high open-mindedness (Karimi & Wagner, 2014). Da Cunha and Greathead (2004) found productivity depends on task type and individual traits (Weinberg, 1998). High agreeableness might favor collaboration, making it less impactful in individual tasks, like in our case. Finally, Karimi & Wagner (2014) found no consistent correlation between personality and programming performance.

We also observed that the data from School A in Research Question 1 and 2 showed a correlation that aligns with the data obtained from both Schools A and B. While differences in curriculum or school culture could play a significant role in this consistency, these factors were not within the scope of the current study and, therefore, were not analyzed in detail. Future research could explore these aspects to provide a deeper understanding of the correlation.

This study suggests that educators might develop strategies that cater to the strengths of agreeable and conscientious students. Collaborative learning, like group projects, pair programming, and peer tutoring, could potentially leverage these students' interpersonal skills. Providing timely feedback could be beneficial for conscientious students, helping them stay organized and perform consistently.

A limitation of this study is its focus on compile errors. While informative, compile errors do not capture all challenges students face. Runtime errors require distinct debugging skills. Future research should investigate these errors, analyze patterns, and create strategies to help novices address them effectively.

Acknowledgements

We thank Ateneo de Manila University and Pangasinan State University administration for allowing us to conduct the experiment for this study.

References

Afshar H, Roohafza HR, Keshteli AH, Mazaheri M, Feizi A, Adibi P. (2015). The association of personality traits and coping styles according to stress level. J Res Med Sci. 2015 Apr;20(4):353-8. PMID: 26109990; PMCID: PMC4468450.

Amin, A., Basri, S., Rahman, M., Capretz, L. F., Akbar, R., Gilal, A. R., Shabbir, M. F. (2020). The impact of personality traits and knowledge collection behavior on programmer creativity. Information and Software Technology. Vol. 128, December 2020, 106405.

Barik, T., Smith, J., Lubick, K., Holmes, E., Feng, J., Murphy-Hill, E., and Parnin, C. (2017). Do Developers Read Compiler Error Messages?. In 2017 IEEE/ACM 39th International Conference on Software Engineering (ICSE) (pp. 575-585).

Chandrika, K. R. and Amudha, J. (2017). An Eye Tracking Study to Understand the Visual Perception Behavior while Source Code Comprehension. *International Journal of Control Theory and Applications*. International Science Press vol. 10(19), 169-175.

da Cunha, A.D. & Greathead, D. (2004). Code review and personality: is performance linked to MBTI type?. University of Newcastle upon Tyne. https://eprints.ncl.ac.uk/file_store/production/55801/F90A364D-9E2A-4EED-BAC5-04F38FBE3D99.pdf

De Young, C. G., Quilty, L. C., & Peterson, J. B. (2007). Between facets and domains: 10 aspects of the Big Five. Journal of Personality and Social Psychology, 93, 880-896

Dirzyte, A., Vijaikis, A., Perminas, A., Rimasiute-Knabikiene, R., Kaminskis, L. and Zebrauskas, G. (2021). Computer Programming E-Learners' Personality Traits, Self-Reported Cognitive Abilities, and Learning Motivating Factors. *Brain Sci*. 2021 Sep; 11(9): 1205.
Goldberg, L. R. (1999). A broad-bandwidth, public-domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. Deary, F. De Fruyt, & Ostendorf (Eds.), Personality Psychology in Europe (Vol. 7, pp. 7-28). Tilburg, The Netherlands: Tilburg University Press
Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist*, 48, 26-34.
Hasanzadeh, S., Dao, B., Esmaeili, B., and Dodd, M.D. (2019). Role of Personality in Construction Safety: Investigating the Relationships between Personality, Attentional Failure, and Hazard Identification under Fall-Hazard Conditions. *Journal of Construction Engineering and Management*, 2019
Hazrati-Viari, A., Rad, A.T. and Torabi, S. S. (2011). The effect of personality traits on academic performance: The mediating role of academic motivation. *Procedia - Social and Behavioral Sciences* 32 (2012) 367 – 371
Hofstee, W. K., De Raad, B., & Goldberg, L. R. (1992). Integration of the Big Five and circumplex approaches to trait structure. Journal of Personality and Social Psychology, 63, 146-163
John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm shift to the integrative Big-Five trait taxonomy: History, measurement, and conceptual issues. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), Handbook of personality: Theory and research (3rd ed., pp. 114- 158). New York, NY: Guilford
Karimi, Z., Baraani-Dastjerdi, A., Ghasem-Aghaee, N. and Wagner, S. (2016). Using Personality Traits to Understand the Influence of Personality on Computer Programming: An Empirical Study. Journal of Cases on Information Technology, Vol. 18, Issue 1, January-March 2016
Karimi, Z. and Wagner, S. (2014). The influence of personality on computer programming: a summary of a systematic literature review. University of Stuttgart. OPUS - Publication Server of the University of Stuttgart. http://dx.doi.org/10.18419/opus-3243
Lucas, R. E., Le, K., & Dyrenforth, P. S. (2008). Explaining the extraversion/positive affect relation: Sociability cannot account for extraverts' greater happiness. Journal of Personality, 76, 385-414
McCrae, R. R., & Costa, P.T. (2008). The Five-Factor Theory of personality. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), Handbook of personality: Theory and research (3rd ed., pp.159-181). New York, NY: Guilford
Nechita, F., Alexandru, D.O., Turcu-Stiolica, R. and Nechita, D. (2015). The Influence of Personality Factors and Stress on Academic Performance. Curr Health Sci J. 2015 Jan-Mar; 41(1): 47–61.
Pacol, C., Rodrigo, M.M. and Tablatin, C.L. (2024). A Comparative Study of High and Low Performing Students' Visual Effort and Attention when Identifying Syntax Errors. Human-Computer Interaction International Conference 2024.
Saucier, G., & Ostendorf, F. (1999). Hierarchical subcomponents of the Big Five personality factors: A cross-language replication. Journal of Personality and Social Psychology, 76, 613-627
Soto, C. J., & John, O. P. (2017). The next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. Journal of Personality and Social Psychology, 113, 117-143.
Tablatin, C.L. and Rodrigo, M.M. (2023). "Visual Attention Patterns in Processing Compiler Error Messages", Proceedings of the 31st International Conference on Computers in Education. Asia-Pacific Society for Computers in Education.
van Berkel H. Canterbury Univ: Thesis of MS in Psychology; (2009). The Relationship Between Personality, Coping Styles and Stress, Anxiety and Depression.
Vasconcelos, L., Arslan-Ari, I. and Ari, F. (2020). Early childhood preservice teachers' debugging block-based programs: An eye tracking study. *Journal of Childhood, Education & Society*, 1(1), 63-77.
Wang, H., Liu, Y., Wang, Z., and Wang, T. (2023). The influences of the Big Five personality traits on academic achievements: Chain mediating effect based on major identity and self-efficacy. Front. Psychol., 27 January 2023 Sec. Personality and Social Psychology, Vol. 14 – 2023
Watson, D., & Clark, L. A. (1997). Extraversion and its positive emotional core. In R. Hogan, J. A. Johnson, & S. R. Briggs (Eds.), Handbook of personality psychology (pp. 767-793). San Diego, CA: Academic Press
Weinberg, G.M., (1998).The psychology of computer programming. 2nd ed. 1998, New York,: Van Nostrand Reinhold. xv, 288.