A Human-Centered Approach to Learning Analytics: Understanding How Personality Traits Shape Learning Activity Engagement

Chathura K. Sooriya-Arachchi[1*] and Hua Claria Guo[2]

[1,2] *Queen Mary University of London, London, United Kingdom*

Abstract

This work-in-progress study adopts a human-centered approach to understanding how individual learner characteristics shape learner engagement and performance in Computer Science education. In an era of increasing digitalisation, learning technologies need to be designed around learner needs and their individual differences. This study examines how learners' Big Five personality traits influence their interactions with different learning design activity types, positioning the learner's individual characteristics at the heart of learning analytics. Analysis of data from a Level 5 Computer Science module (n=72) revealed distinct personality distributions, with Openness (63%) and Agreeableness (32%) being predominant traits. Learning activity completion patterns varied significantly from high engagement in interactive activities (100%) to lower engagement in communication tasks (7.77%). Correlation analysis revealed significant relationships between personality traits and learning behaviours, with Conscientiousness positively correlating with assessment engagement and Neuroticism showing consistent negative correlations across activities. These findings provide crucial insights for designing more inclusive and personalised learning environments, suggesting the need for flexible learning pathways that accommodate different personality profiles while maintaining academic rigour. This research represents a crucial step toward educational technologies that focus on understanding and responding to individual learner needs, potentially transforming how educators approach Computer Science Education.

Keywords

human-centered learning analytics, personality traits, learner engagement, personalised learning, computer science education

1. Introduction

Learning analytics in higher education has evolved significantly, with Virtual Learning Environments (VLE) becoming central to understanding and supporting student learning [1], [2]. While these platforms generate extensive data about learner interactions [3], [4], current implementations often prioritise technological capabilities over human factors [5]. There remains a critical gap between collecting learning analytics data and using it effectively to create personalised learning experiences [6], particularly in understanding how individual learner characteristics influence engagement with different types of learning activities [7]. Despite VLEs generating vast amounts of learner interaction data, this data is rarely used to create truly personalised, human-centered learning experiences [8] that account for the complex interplay between learner personality and engagement dynamics. This study addresses this gap by examining how personality traits influence student engagement levels with different types of learning activities in a Computer Science education context.

Modern VLE platforms serve as learning environments that can collect comprehensive data on learner engagement and learning patterns [9],[10]. Educators manage these learning environments to offer various learning design activities, from assimilative (e.g. reading, watching) to interactive (e.g. exploring, experimenting) tasks. However, the human-centered challenge lies in understanding

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[1*] Corresponding author.
c.k.sooriyaarachchi@qmul.ac.uk (C. K. Sooriya-Arachchi); claria.guo@qmul.ac.uk (H. C. Guo)
0009-0003-2233-5792 (C. K. Sooriya-Arachchi); 0000-0002-4089-8834 (H. C. Guo);

how different learners engage with these activities based on their individual characteristics and preferences [11]. Research has demonstrated that personality traits fundamentally shape how learners approach and engage with learning. The Big Five personality traits - particularly conscientiousness, openness to experience, extraversion, and agreeableness - significantly influence both self-regulated learning and academic engagement [12]. Conscientiousness especially emerges as a crucial trait, contributing to academic achievement through self-regulation and goal-oriented behaviour [13]. Understanding these personality-based learning patterns is essential for creating adaptive learning environments that respond to individual learner needs [14]. This study adopts a human-centered learning analytics approach to examine how learner personalities influence engagement levels with different types of learning activities. By understanding these relationships, this study aims to bridge the gap between learning analytics and human-centered design, contributing to more personalised and effective learning experiences.

Recent work has highlighted how causal modelling can bridge the gap between learning analytics and educational theory [15], [16]. While correlational analysis provides insights into relationships between personality traits and learning behaviours, understanding potential causal mechanisms requires careful theoretical grounding in established frameworks like self-regulated learning theory. This study draws on self-regulated learning theory to examine how personality traits influence learning dynamics such as learner engagement and performance. For instance, how conscientiousness may affect assessment engagement levels through enhanced goal setting and time management, openness likely influences exploratory learning through increased intrinsic motivation, and extraversion's relationship with interactive activities aligns with social learning preferences.

Based on these foundations, this study addresses the following research question with the associated research objective:

RQ-1: How do different personality traits influence engagement patterns across various learning design activities?

RO-1: Examine the relationship between learner personality traits and learning design activity types.

However, these relationships manifest differently across learning contexts and would require critical examination.

2. Methodology

This study examined personality traits and learner engagement levels in a Level 5 Software Engineering module at Queen Mary University of London. Learning analytics were captured through VLE logs tracking learner interactions with a total of 100 learning activities, categorised according to the OULDI learning design taxonomy [11] into assimilative, find and handle information, communication, productive, experiential, interactive, and assessment activities. The Big Five Indicator (BFI) personality traits questionnaire [15] was administered at the module start, while activity completion logs, though a coarse-grained measure, were extracted weekly, and gradebook data were collected at semester end. Learner identification data were anonymised before analysis of relationships between personality traits, engagement patterns, and performance markers.

3. Preliminary Results and Discussion

Analysis of BFI personality traits questionnaire responses (n=72) revealed distinct patterns in learner personality distributions. The majority of learners exhibited high 'Openness' (63%), followed by 'Agreeableness' (32%), while 'Conscientiousness' (10%), 'Neuroticism' (4%), and 'Extroversion' (1%) were less prevalent.

The dominance of *Openness* (63%) suggests a cohort characterised by intellectual curiosity, likely to engage well with exploratory learning activities, while moderate *Agreeableness* (32%) indicates potential for effective collaborative learning. The limited representation of *Conscientiousness* (10%)

signals a need for structured guidance and explicit deadlines, while low levels of *Neuroticism* and *Extroversion* suggest a predominantly introverted cohort preferring individual work.

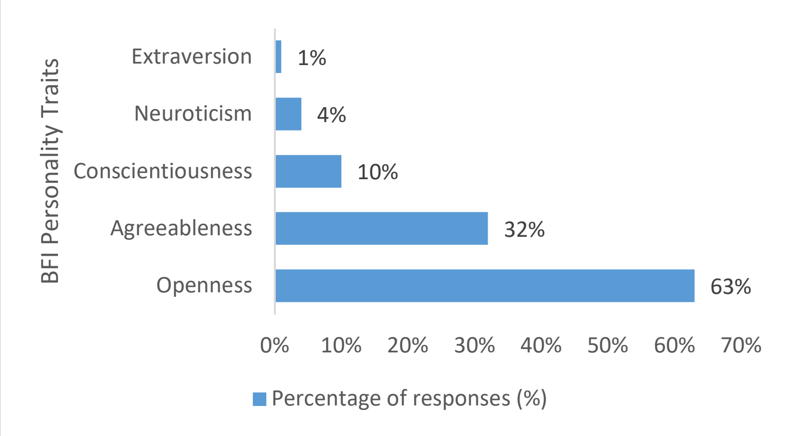

Figure 1 - Distribution of BFI personality traits among learners

These personality distributions inform learning design approaches, suggesting a curriculum that balances discovery-based activities with clear support in organisation. This is supported by activity completion patterns, where interaction-type activities showed highest engagement (100%), followed by assessment (65.02%), productive/experiential activities (16.83%), assimilative activities (16.28%), with finding and handling information (14.84%), while communication (7.77%) showed lower engagement levels.

Table 1 - activity completion across LD activity types

Activity Type	Completion Rate (%)	Standard Deviation	Skewness
Interactive	100	3.391	0.6835
Assessment	65.02	3.208	0.566
Productive	16.83	0.4055	-0.9345
Experiential	16.83	0.4055	-0.9345
Assimilative	16.28	0.6074	0.4635
Find Handle Info	14.84	0.4242	-0.3893
Communication	7.77	0.2861	-0.1909

Correlation analysis between personality traits and learning activities revealed the following key relationships. *Conscientiousness* correlated positively with assessment activities ($r = 0.24$, $p < 0.05$), reinforcing the expectation that conscientious learners engage more with structured assessments. *Extraversion* correlated positively with interactive activities ($r = 0.21$, $p < 0.05$) and communication activities ($r = 0.19$, $p < 0.05$), reflecting a preference for social engagement and collaborative tasks. *Neuroticism* showed a negative correlation with most activity types, particularly productive ($r = -0.27$, $p < 0.05$) and assessment ($r = -0.23$, $p < 0.05$), likely due to anxiety and avoidance behaviours. *Openness* did not show a significant correlation with engagement metrics, indicating that while students high in openness may prefer exploratory learning, their overall engagement levels vary significantly across different tasks.

Table 2 - BFI traits vs. LD activity completion Correlation Matrix

	Assimilative	Find Handle Info	Communication	Productive	Experiential	Interactive	Assessment
Openness	0.05	0.08	0.02	0.1	0.12	0.07	0.15
Conscientiousness	0.12	0.18	0.09	0.14	0.17	0.1	0.24
Extraversion	0.03	0.05	0.19	0.07	0.08	0.21	0.11
Agreeableness	0.09	0.11	0.13	0.1	0.14	0.09	0.18
Neuroticism	-0.07	-0.12	-0.1	-0.27	-0.22	-0.14	-0.23

[H1] *Conscientiousness* showed the strongest positive correlation with assessment completion ($r = 0.24$, $p < 0.05$), which aligns with expectations given conscientious learners' tendency for organisation and achievement orientation. Also, [H2] *Extraversion* demonstrated significant positive correlations with both interactive ($r = 0.21$, $p < 0.05$) and communication activities ($r = 0.19$, $p < 0.05$), supporting theoretical expectations about extraverts' preference for social interaction. Interestingly [H3] *Neuroticism* showed consistent negative correlations across activity types, most notably with productive activities ($r = -0.27$, $p < 0.05$) and assessment tasks ($r = -0.23$, $p < 0.05$), which aligns with expected impacts of anxiety and stress on engagement.

These findings, supported by the overall strong module performance ($M = 82.49\%$, $SD = 7.68$) and negative skewness (-1.193) in grade distribution, suggest several concrete approaches for personalisation while maintaining pedagogical effectiveness:

1. Assessment Design: Provide clear structure for high-neuroticism learners while maintaining academic rigour, given the significant negative correlation with assessment activities
2. Learning Activity Types: Offer multiple paths through learning materials that accommodate different personality profiles, particularly noting the varying engagement levels from interactive (100% completion) to communication (7.77% completion) activities
3. Support Mechanisms: Implement adaptive scaffolding based on personality traits while ensuring all learners can access core content, with particular attention to supporting highly neurotic learners across all activity types
4. Participation Methods: Create flexible engagement options and deadlines without compromising learning objectives, considering the varied standard deviations in engagement across activity types

However, personality-based adaptations must be implemented thoughtfully, as traits manifest differently across contexts and activity completion rates alone may not capture full engagement patterns, and wholesale changes to learning design based solely on personality type may not be appropriate. This is particularly important given the peaked distribution of grades (kurtosis = 5.067) suggesting current approaches are generally effective while leaving room for targeted improvements.

4. Conclusion

This study reveals significant implications for learning design and curriculum development, with statistical evidence demonstrating how personality traits influence learner engagement and performance levels. Study analysis revealed strong correlations between personality traits and specific learning activities, particularly in assessment engagement levels and varied activity completion rates (7.77%-100%).

Study findings emphasise the need for institutions to develop personalised learning pathways that accommodate different personality traits through flexible learning structures and systematic learning analytics integration. Support systems should include scaffolding mechanisms and monitoring tools tailored to different personality types, with continuous data collection informing teaching strategies and interventions. Implementation should focus on creating dynamic, responsive curriculum structures that maintain academic rigour while enabling early identification of at-risk learners.

Future work could explore more granular interaction data and refined engagement measures to develop a more nuanced understanding of personality-engagement relationships in Computer Science education.

5. Declaration on Generative AI

The authors declare that no generative artificial intelligence (GenAI) tools were used in the writing, editing, or production of this paper.

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