Personality, Distractions, and Early IDE Metrics as Predictors of Introductory Programming Performance

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Abstract. *Introductory Programming Classes (IPC) often exhibit failure rates between 30% and 50%, motivating investigations on factors that may influence learning, not only cognitive but non-cognitive factors as well. We report an empirical study with two cohorts of Information Systems students (N=64), contrasting first-time learners (Class 1) and students repeating the course (Class 2). We combined three data sources: Big Five traits measured with Mini-IPIP, a lab-focused questionnaire on self-perceived internal/external distractions, and fine-grained CodeBench IDE logs (e.g., typing activity and successful submissions). Results indicate that associations are context-dependent: internal distractions hindered programming outcomes for novices, conscientiousness was highly correlated with academic success for Class 1, and openness to experience indicated early performance for Class 2. Across both classes, early IDE metrics were important predictors of later grades and GPA. After False Discovery Rate Correction (FDR), we found no evidence that personality moderates the distraction-performance relationship.*

1. Introduction

IPC are foundational in computing curricula, but they consistently show high failure and withdrawal rates [Mehmood et al. 2020, Margulieux et al. 2020]. Beyond cognitive demands, students must manage interruptions that compete for limited attentional resources and increase extraneous cognitive load [Brady et al. 2021, Deng et al. 2024]. In parallel, personality traits (e.g., conscientiousness) are important predictors of academic performance across domains [Mammadov 2022]. However, in programming education, it is still unclear how stable individual differences (personality) relate to situational obstacles (distractions) and to observable learning behaviors captured by learning analytics systems [Pereira et al. 2020, Llanos et al. 2023].

This paper presents an investigation of the relationships between Big Five traits, self-perceived distractions, and performance in IPC, while comparing two distinct contexts: novices vs. repeaters. The central premise is that the “same” non-cognitive factor may manifest differently depending on prior experience, motivation, and familiarity with course demands.

2. Method

Participants. We analyzed two cohorts of undergraduate Information Systems students enrolled in IPC at a Brazilian public university: Class 1 (first-time learners) and Class 2 (mostly repeating students), with 32 students per class (N=64).

Instruments. Personality was measured with Mini-IPIP [Donnellan et al. 2006], using the Portuguese adaptation by [Oliveira 2019]. Distractions were measured with an 11-item questionnaire designed by us, synthesizing prior categorizations of digital, social/environmental, and internal distractions [Brady et al. 2021, Dontre 2021, Deng et al. 2024]. Students also used CodeBench, an online judge and IDE that records detailed interaction events and submissions [Institute of Computing, Federal University of Amazonas 2025].

Procedure and data. Data collection occurred during supervised programming labs focused on introductory topics (e.g., conditionals, loops, and arrays). We kept only lab session logs to reduce noise from out-of-class work (students were allowed to finish at home). The dataset combines questionnaire responses, course outcomes (exams and GPA), and engineered IDE features derived from CodeBench event logs (e.g., successful submissions, submission success rate, typing activity, and total events).

Analysis. We used Spearman correlations to explore associations among traits, distractions, IDE metrics, and academic outcomes. We then fit regression models to identify class-specific predictors of IDE behaviors and outcomes. Finally, we tested whether personality traits moderate the association between distractions and performance using interaction models, applying FDR correction for multiple comparisons.

3. Results and Discussion

Overall, results were class-dependent.

Distractions and programming behavior. For novices (Class 1), internal distractions were consistently linked to worse lab performance (e.g., lower correctness and lower submission success). In regression models, internal distractions negatively predicted submission success rates ($\beta \approx -0.46$) and overall correctness ($\beta \approx -0.69$). For repeaters (Class 2), distraction variables did not show significant independent effects in regression, and bivariate patterns suggested a different relationship between perceived distractions and performance, potentially reflecting alternative coping strategies and familiarity with course demands.

Personality and academic outcomes. In Class 1, conscientiousness was the main personality indicator of achievement (positive association with exam and GPA), reinforcing the role of persistence and self-regulation in early programming learning [Mammadov 2022]. In Class 2, openness to experience correlated with early exam performance, suggesting that intellectual flexibility and willingness to explore alternatives may be critical for re-engagement after prior failure.

Early IDE metrics as predictors. Across both classes, early IDE metrics were important predictors of final performance, corroborating prior work on early risk detec-

Table 1. Condensed findings by class (main effects).

Aspect	Class 1 (novices)	Class 2 (repeaters)
Distractions	Internal distractions associated with lower correctness and success in CodeBench.	Distractions not significant as independent predictors in regression models.
Personality	Conscientiousness associated with higher GPA/exam performance.	Openness to experience associated with higher early exam performance.
Early IDE metrics	Successful submissions and typing activity predict later grades/GPA.	Typing activity and overall engagement (events/duration) predict GPA/pass.
Moderation	None after FDR correction.	None after FDR correction.

tion in CS1 [Pereira et al. 2020, Llanos et al. 2023]. For novices, metrics related to early success (notably successful submissions) were among the strongest indicators of later GPA and exam grades. For repeaters, engagement proxies such as typing activity and total events/duration were consistently correlated with GPA and pass/fail outcome.

No robust moderation effects. Despite extensive testing, no personality $\times$ distraction interaction remained significant after FDR (or Bonferroni) correction, indicating that, in this sample, main effects are more detectable than moderation effects.

4. Conclusion

This study suggests that non-cognitive factors in IPC should be interpreted in light of prior course experience. For novices, reducing internal distractions and supporting persistence (aligned with conscientiousness) may improve outcomes. For repeaters, interventions may benefit from fostering exploratory learning strategies and cognitive flexibility (aligned with openness). In both contexts, early IDE metrics, particularly those capturing early success and sustained engagement, are promising signals for early identification of at-risk students, enabling timely interventions.

Limitations. Results are based on a single institution and a modest sample size, and distractions were self-reported with an instrument that still requires psychometric validation. Future work should triangulate distractions with objective signals (e.g., gaze or focus inference) and replicate findings across semesters and institutions.

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