An Empirical Investigation of Personality Traits, Self-Perceived Distractions, and Programming Performance in an Introductory Programming Class

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Abstract. *We investigated the interrelationships between personality traits, self-perceived distractions, and programming performance in an introductory programming class (IPC). Thirty-two undergraduate students participated in personality assessments and programming exercises on an Integrated Development Environment (IDE) platform that captured detailed behavioral interactions. We found that conscientiousness—one of the personality traits—was the strongest predictor of academic success, such as Grade Point Average (GPA). Internal distractions were significantly associated with reduced programming performance. Several IDE metrics strongly predicted academic performance, with successful submissions correlating highly with GPA. After applying False Discovery Rate correction (FDR) for multiple testing, no personality-distraction interactions remained statistically significant among the 190 moderation tests conducted, suggesting that apparent moderation effects may be attributable to chance. In our work, personality traits showed weak associations with distractions, potentially due to bias inherent in self-report measures. Our findings suggest that programming interventions should prioritize conscientiousness-based self-regulation training and internal distraction management, while some of the IDE behavioral patterns can serve as predictors for identifying at-risk students.*

1. Introduction

Computer science and related field students often encounter Introductory Programming Classes (IPCs) as a turning point in their academic lives. These classes are, however, notoriously challenging, often associated with high dropout and failure rates, which can range between 30% and 50% [Margulieux et al. 2020, Mehmood et al. 2020]. IPCs' high demands, requiring complex problem-solving abilities and abstract thinking, impose extraneous cognitive loads on novice learners [Winkler and Flatscher 2023]. Understanding these factors that influence student success is therefore an essential component for developing effective pedagogical strategies and support mechanisms.

In addition to other factors, classroom and digital distractions impair learning through extraneous cognitive load [Paas and Van Merrienboer 2020,

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Flanigan and Babchuk 2022]. Concurrently, individual differences, particularly personality traits as described by the Big Five Model, are known to influence academic performance and how students manage learning environments [Mammadov 2022]. The interaction between students' personalities and their susceptibility to distractions can further complicate their learning experience, especially in complex tasks like programming [Mark et al. 2018].

The impact of personality and distractions on programming performance has been studied before; however, studies have not yet investigated the relationship among all three factors simultaneously. Therefore, we aim to investigate the interrelationships between self-perceived distractions, acquired from the questionnaire; personality traits, also from the questionnaire; and programming behavior to better understand the dynamics affecting student performance in IPCs. Specifically, we seek to understand how these factors collectively and individually relate to academic performance in an introductory programming class. We address the following research questions (RQ):

RQ1: What is the relationship between Big Five personality traits and students' self-perceived internal and external distractions in an IPC? Are there any?

RQ2: How do self-perceived internal and external distractions and individual personality traits relate to observable programming behaviors in the Integrated Development Environment (IDE), and to what extent can these behaviors predict academic performance?

2. Theoretical Background

This section covers the cognitive impact of distractions, the Big Five personality traits and their links to academic performance, and how personality influences distraction management by students. It also outlines programming performance indicators from IDE—a software application that integrates code writing, execution, and debugging capabilities into a single environment—data and introduces CodeBench, the platform used for data collection.

2.1. Distractions and Cognitive Impact

Distractions can be divided into internal and external. External distractions come from the environment, mostly due to technological devices, social media, noise, and other people [Dontre 2021, Deng et al. 2024, Brady et al. 2021]. Internal distractions originate from within the individual. These include, but are not limited to, mind-wandering, becoming bored, feeling anxious, and getting exhausted [Brady et al. 2021, Esterman and Rothlein 2019, Deng et al. 2024].

Classroom distractions negatively impact learning by imposing extraneous cognitive load on students' limited working memory capacity [Paas and Van Merrienboer 2020]. Digital distractions are prevalent in 70-90% of college classrooms, with students often involved in off-task behaviors like texting and social media use [Flanigan and Babchuk 2022]. Distractions divide cognitive resources between the learning task and the distraction, meaning fewer mental resources are available for understanding the subject [Chandler and Sweller 1991]. Research shows that distraction is negatively correlated with learning, performance, and Grade Point Average (GPA) [Flanigan and Babchuk 2022, Dontre 2021].

2.2. Personality Traits and Academic Performance

According to Mammadov [Mammadov 2022] the Big Five is a theoretical framework used to synthesize variations in personality traits, which are defined as relatively stable patterns of cognitions, beliefs, and behaviors. The five traits are labeled as openness, which is a degree of intellectual curiosity, creativity, and preference for novelty and variety; conscientiousness, a tendency to show self-discipline, planning, and organization; extraversion, which includes positive emotions, activity, sociability, and the tendency to seek stimulation in the company of others; agreeableness, a tendency to be prosocial and cooperative toward others; and neuroticism, the vulnerability to unpleasant emotions such as anxiety, anger, and depression.

Conscientiousness emerges as the strongest personality predictor of academic performance, reflecting organization, self-discipline, and achievement motivation [Mammadov 2022, Zell and Lesick 2022]. Openness to experience shows positive associations with academic outcomes, particularly for tasks requiring creativity and complex thinking [Mammadov 2022, Zell and Lesick 2022].

2.3. Personality-Distraction Interactions

Personality traits moderate how individuals perceive and manage distractions. Less conscientious individuals benefit more from external distraction management tools, suggesting greater self-regulation difficulties [Mark et al. 2018]. Those high in emotional stability report fewer distractions, while neurotic individuals show greater susceptibility to distraction under stress [Seddigh et al. 2016, Eysenck and Graydon 1989].

These personality-distraction interactions are context-dependent, varying based on distractor type, environmental factors, and task demands.

2.4. Programming Performance Indicators

Programming performance encompasses solution correctness, task completion rates, and behavioral indicators derived from IDE data [Llanos et al. 2023, Pereira et al. 2020]. Key metrics include compilation patterns, submission timing, error management strategies, and editing behaviors that reveal problem-solving approaches and engagement levels [Pereira et al. 2021].

Programming comprehension activates brain regions associated with working memory, sustained attention, and language processing [Peitek et al. 2018], making it particularly vulnerable to attention-disrupting distractions. Understanding these factors' relationships provides a framework for our investigation of student success in introductory programming classes.

2.5. CodeBench Platform

The CodeBench [1] is a platform for automatic assessment of programming exercises developed at the Federal University of Amazonas. The system functions as an online judge where students write, test, and submit code solutions and receive instant automated feedback.

[1] URL: https://cb.icomp.ufam.edu.br/

A notable distinction of the platform is its thorough data logging system, which tracks detailed student activity like keystrokes, mouse movements, submission attempts, and coding behavior in the IDE. This rich dataset enables research studies on student performance prediction and educational effectiveness [Coelho et al. 2023].

3. Methodology

This section outlines the methodological approach we employed in this study, as shown in Figure 1. We detail the characteristics of the participants, ethical considerations, the instruments we utilized for data collection, the procedures we followed for data gathering, and the methods we applied for data pre-processing and subsequent statistical analysis.

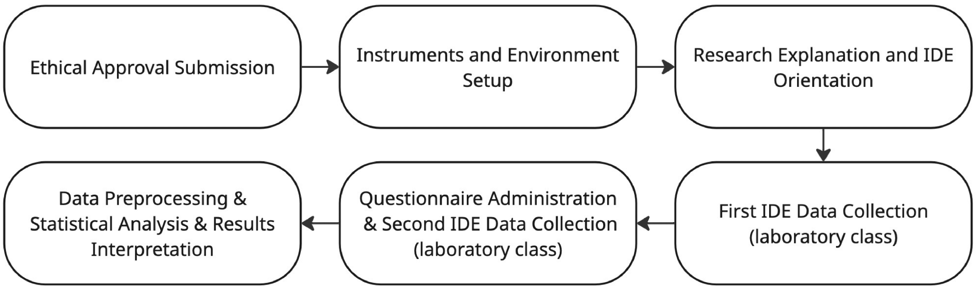

Figure 1. Overview of the research process.

3.1. Participants and Ethical Considerations

We used the data from 32 undergraduate Information Systems students from an introductory programming class who completed all study requirements, selecting them from an initial pool of 64 students. Participants were aged 18 to 50, with a majority aged 18 to 25.

The group included first-time university students and individuals with prior diplomas and professional experience in diverse fields, including programming, healthcare, and engineering. Some variation in initial programming proficiency was also present; some students already had programming knowledge, while some had never programmed before.

The study was conducted with ethical approval from the Research Ethics Committee[2] and informed consent was obtained from all participants.

3.2. Instruments

We collected data using two instruments. The first was an online questionnaire administered via Google Forms to collect data on self-perceived distractions (11 items) and personality traits (20 items). Personality was assessed using the Mini-IPIP, a concise yet effective measure of the Big Five personality factors [Donnellan et al. 2006]. Both sections of the questionnaire utilized a 5-point Likert scale, with an additional "prefer not to answer" option. The Mini-IPIP questions were adapted from the Portuguese version [Oliveira 2019].

[2]CAAE: 82543524.1.0000.5152

The second instrument was the CodeBench, a cloud-based IDE. We used this platform for practical programming exercises focusing on conditional structures, loops, and arrays. The platform was configured to log detailed student interactions, including keystrokes, mouse clicks, code submissions, and browser/IDE window changes, all with corresponding timestamps.

3.3. Procedure

We conducted data collection in two steps. First, students were familiarized with the CodeBench during a single lab session. In a subsequent lab session, the online questionnaire was made available on Microsoft Teams for completion at home.

Programming activities were conducted on CodeBench over two days—one before and one after the first exam—consisting of two 50-minute monitored lab sessions (100 minutes total). Only data from these in-lab sessions were used, while data from exercises done at home were excluded.

3.4. Data Collection and Pre-processing

We stored the questionnaire data (CSV) and the CodeBench logs (JSONL) in the cloud with access restricted to the authors. Student data were anonymized using unique IDs. We conducted pre-processing in Python on Google Colab, converting the questionnaire and CodeBench data to a DataFrame.

Participants with over five missing questionnaire items were excluded. For up to five missing items, mean imputation was applied based on the mean value of other users' responses for that specific question. We parsed the CodeBench logs and performed feature engineering to derive more interpretable variables of programming behavior.

Following this, the 11 items about distraction were divided into two categories: internal and external distractions. We then calculated and normalized levels of internal and external distractions for each participant, since the number of items for each category was imbalanced. Finally, personality traits from Mini-IPIP were calculated for each student.

3.5. Statistical Analysis

Following pre-processing, we merged the questionnaire and CodeBench datasets using students' IDs, which were generated as universally unique identifiers (UUIDs). This merged dataset was then combined with students' exam scores and final GPAs.

We calculated Spearman correlation coefficients (ρ) to assess relationships between: (a) personality and perceived distractions; (b) personality, perceived distractions, and IDE variables; (c) personality, perceived distractions, and academic performance; and (d) IDE variables and academic performance. Furthermore, we employed multiple regression to determine if perceived distraction variables or personality traits predicted IDE interaction variables.

Finally, we used Ordinary Least Squares (OLS) regression to investigate whether personality traits moderated the impact of perceived internal and external distractions on academic performance variables (e.g., GPA), with False Discovery Rate (FDR) correction applied to control for multiple testing across the 190 moderation tests conducted.

4. Results

The results are organized into two main analyses: Spearman correlations to explore bivariate associations, followed by regression analyses to examine predictive relationships and moderation effects. Table 1 describes the variables to better understand the results.

4.1. Spearman Correlations

We performed Spearman correlations to assess the relationships between, first, personality dimensions and measures of internal and external distractions; second, how both personality and distractions correlate with various IDE usage metrics; third, the links between academic performance, distractions, and personality traits; and finally, the association between early IDE metrics and subsequent academic performance. The scale used for interpretation of the correlation strengths was derived from [Schober et al. 2018].

4.1.1. Personality Dimensions and Distractions

The Spearman correlation analysis revealed predominantly weak, non-significant (p-value) relationships between distraction measures and Big Five personality traits (Table 2). Only one statistically significant correlation emerged: agreeableness positively correlated with conscientiousness ($\rho = 0.361$, $p = 0.043$), representing a medium-strength relationship.

Neither internal nor external distractions demonstrated significant associations with any personality dimensions. The strongest trends were external distractions with neuroticism ($\rho = 0.272$, $p = 0.132$) and internal distractions with agreeableness ($\rho = 0.297$, $p = 0.099$), both non-significant.

These findings—using our data—suggest that distraction susceptibility operates largely independently of basic personality traits, indicating that factors beyond the Big Five model may more strongly influence individual differences in distraction vulnerability.

4.1.2. Personality, Distractions, and IDE metrics

The analysis of IDE metrics revealed distinct patterns for how distractions and personality traits are associated with programming behavior (Table 3). Internal distractions were significantly associated with reduced programming performance, showing negative correlations with successful submissions ($\rho = -0.351$, $p = 0.049$), success rates ($\rho = -0.424$, $p = 0.016$), and code correctness ($\rho = -0.423$, $p = 0.016$), suggesting a potential relationship between internal distractions and programming processes. In contrast, external distractions were primarily associated with reduced coding activity intensity ($\rho = -0.375$, $p = 0.035$) rather than directly affecting programming performance measures.

Personality traits were associated with distinct coding patterns. Conscientiousness correlated with more extensive typing activity ($\rho = 0.419$, $p = 0.017$), while extraversion and agreeableness both correlated with increased submission frequency ($\rho = 0.349$, $p = 0.050$ and $\rho = 0.372$, $p = 0.036$ respectively). Neuroticism was associated with indicators

Table 1. Variable Definitions and Descriptions

Variable Name	Description
Personality Traits (Big Five)	
Agreeableness	Tendency to be cooperative, trusting, and considerate in interpersonal relationships
Conscientiousness	Degree of organization, self-discipline, and goal-directed behavior
Extraversion	Level of sociability, assertiveness, and tendency to seek stimulation from external sources
Neuroticism	Emotional instability, anxiety, and tendency to experience negative emotions
Openness	Willingness to experience new ideas, creativity, and intellectual curiosity
Distraction Measures	
Internal Distractions	Mind-wandering, daydreaming, and internally-generated attention lapses
External Distractions	Environmental interruptions, noise, and externally-generated attention disruptions
IDE Metrics	
Typing Activity / Typing Events / Typing Behaviors	Frequency and intensity of keyboard typing actions during programming sessions
Successful Submissions / Total Successful Submissions	Number of code submissions that compiled and executed correctly
Success Rates / Submission Success Rates	Percentage of submissions that were successful out of total attempts
Code Correctness / Overall Correctness	Accuracy and quality of submitted code solutions
Activity Rates / Event Activity	General level of engagement and interaction with the IDE environment
Coding Activity Intensity	Measure of how actively engaged students are during programming tasks
Submission Frequency	Rate at which students submit their code for evaluation
Pause Duration	Length of time between programming actions, indicating workflow interruptions
Academic Performance Measures	
Exam 1	Performance score on the first course examination
Exam 2	Performance score on the second course examination
Exam 3	Performance score on the third course examination
GPA	Overall Grade Point Average in the course
Succeeding in the class	Binary outcome indicating whether the student passed the course

Table 2. Spearman Correlations: Personality Dimensions and Distractions

Variable Pair	ρ	p**-value**
Agreeableness - Conscientiousness	0.361	0.043*
External Distractions - Neuroticism	0.272	0.132
Internal Distractions - Agreeableness	0.297	0.099

*Significant at $p < 0.05$

of less smooth coding flow, including reduced activity rates ($\rho = -0.402$, $p = 0.022$) and longer pauses between actions ($\rho = 0.351$, $p = 0.049$).

These findings suggest that internal distractions may be more strongly associated with programming performance than external interruption control.

Table 3. Spearman Correlations: Distractions, Personality Traits, and IDE Metrics

Variable Pair	ρ	p**-value**
Internal Distractions and IDE Metrics		
Internal Distractions - Successful Submissions	-0.351	0.049*
Internal Distractions - Success Rates	-0.424	0.016*
Internal Distractions - Code Correctness	-0.423	0.016*
External Distractions and IDE Metrics		
External Distractions - Coding Activity Intensity	-0.375	0.035*
Personality Traits and IDE Metrics		
Conscientiousness - Typing Activity	0.419	0.017*
Extraversion - Submission Frequency	0.349	0.050*
Agreeableness - Submission Frequency	0.372	0.036*
Neuroticism - Activity Rates	-0.402	0.022*
Neuroticism - Pause Duration	0.351	0.049*

*Significant at $p < 0.05$

4.1.3. Performance, Distractions, and Personality

The analysis of academic performance revealed conscientiousness as the strongest correlate of academic success, with significant positive correlations for exam 3 ($\rho = 0.392$, $p = 0.026$) and overall GPA ($\rho = 0.421$, $p = 0.016$). In contrast, distractions showed minimal associations with academic outcomes (Table 4).

Neither internal nor external distractions significantly correlated with exam scores, GPA, or succeeding in the class, with the largest distraction effect being only $\rho = -0.185$ for internal distractions on exam 2 ($p = 0.311$). Other personality traits showed non-significant trends, with neuroticism exhibiting consistent negative patterns and agreeableness/extraversion showing weak positive associations with GPA, both non-significant.

These findings suggest that academic performance may be more buffered against momentary distractions than real-time tasks, emphasizing that conscientiousness-related behaviors showed stronger associations with academic success than managing momentary attention lapses.

Table 4. Spearman Correlations: Academic Performance and Personality Traits

Variable Pair	ρ	p-value
Conscientiousness - Exam 3	0.392	0.026*
Conscientiousness - GPA	0.421	0.016*
Internal Distractions - Exam 2	-0.185	0.311

*Significant at $p < 0.05$

4.1.4. Performance and IDE metrics

The analysis of early IDE metrics revealed strong correlational relationships with subsequent academic performance, with successful submissions emerging as the strongest correlate across all measures (Table 5). Total successful submissions showed very high correlation with exam 3 performance ($\rho = 0.698$, $p < 0.001$) and high correlation with GPA ($\rho = 0.636$, $p < 0.001$), indicating that early programming success was strongly associated with later achievement.

Coding activity intensity, measured through typing events, demonstrated consistent high correlations with exam 3 ($\rho = 0.589$, $p < 0.001$) and GPA ($\rho = 0.569$, $p < 0.001$), suggesting that engaged programming behavior was strongly associated with better learning outcomes. Performance metrics also proved strongly associated, with submission success rates correlating significantly with exam 2 ($\rho = 0.496$, $p = 0.004$), exam 3 ($\rho = 0.475$, $p = 0.006$), and GPA ($\rho = 0.432$, $p = 0.014$).

Particularly, exam 3 emerged as the most strongly associated outcome with early IDE behavior, while exam 1 showed weaker correlations. This indicates that programming metrics may become more predictive as course complexity increases and foundational concepts accumulate.

Table 5. Spearman Correlations: Early IDE Metrics and Academic Performance

Variable Pair	ρ	p-value
Successful Submissions - Exam 3	0.698	< 0.001*
Successful Submissions - GPA	0.636	< 0.001*
Typing Events - Exam 3	0.589	< 0.001*
Typing Events - GPA	0.569	< 0.001*
Success Rates - Exam 2	0.496	0.004*
Success Rates - Exam 3	0.475	0.006*
Success Rates - GPA	0.432	0.014*

*Significant at $p < 0.05$

4.2. Regression

We outline the findings from the regression analyses we conducted. We employed multiple regression models to determine the independent contributions of personality traits and distractions to IDE metrics and academic performance. Additionally, we performed moderation analyses to investigate whether specific personality traits alter the impact of distractions on the measured outcomes.

4.2.1. Multiple Regression Analysis

The multiple regression analysis (Table 6) revealed that internal distractions emerged as the most robust predictor, maintaining nearly identical effect sizes when controlling for personality and external factors. Internal distractions significantly predicted reduced submission success rates ($\beta = -0.461, p = 0.017, R^2 = 0.354$) and lower overall correctness ($\beta = -0.688$, $p = 0.023$, $R^2 = 0.303$), confirming their independent causal influence on learning quality.

Among personality traits, extraversion demonstrated significant independent effects on behavioral engagement, predicting increased typing activity ($\beta = 574.48$, $p = 0.042$, $R^2 = 0.454$) and successful submissions ($\beta = 1.926, p = 0.046$, $R^2 = 0.396$). Conscientiousness enhanced typing behaviors ($\beta = 682.74$, $p = 0.050$, $R^2 = 0.454$), with ElasticNet regularization confirming the importance of these relationships through consistent variable selection across models.

It is important to note that external distractions showed no significant independent effects in the multiple regression framework. The substantial overfitting evidence (average adjusted $R^2 = -0.018$) highlighted the limitations of complex modeling with small sample sizes ($N = 32$).

Table 6. Multiple Regression Results: Internal Distractions and Personality Traits as Predictors

Predictor - Outcome	β	p-**value**	R^2
Internal Distractions as Predictor			
Internal Distractions - Submission Success Rates	-0.461	0.017*	0.354
Internal Distractions - Overall Correctness	-0.688	0.023*	0.303
Personality Traits as Predictors			
Extraversion - Typing Activity	574.48	0.042*	0.454
Extraversion - Successful Submissions	1.926	0.046*	0.396
Conscientiousness - Typing Behaviors	682.74	0.050*	0.454

*Significant at $p < 0.05$

4.2.2. Personality Traits as Moderators

To investigate whether personality traits moderate the relationship between distractions and programming outcomes, we conducted a comprehensive analysis of 190 interaction tests across all combinations of personality traits, distraction types, and outcome variables. Given the large number of tests, we applied False Discovery Rate (FDR) correction to control for multiple comparisons.

Before correction, 14 interactions showed statistical significance at $p < 0.05$ (7.4% of tests), which slightly exceeded the 9.5 interactions expected by chance alone (5% false positive rate). However, after applying FDR correction with $q = 0.05$, zero interactions remained statistically significant, indicating that the apparent moderation effects were likely false positives resulting from multiple testing.

The uncorrected results had suggested patterns such as conscientiousness moderating internal distractions (6 apparent effects) and openness showing vulnerability to external distractions (4 apparent effects). However, these patterns did not survive appropriate statistical correction and should be considered exploratory observations requiring replication in larger samples rather than confirmed findings. Table 7 summarizes the comprehensive moderation analysis, highlighting the critical impact of multiple testing correction on interpretation.

Table 7. Multiple Testing Correction Results for Moderation Analysis

Testing Outcome	Count
Total moderation tests conducted	190
Uncorrected significant interactions ($p < 0.05$)	14 (7.4%)
Expected false positives (5% rate)	9.5
FDR-corrected significant interactions ($q < 0.05$)	0 (0%)
Bonferroni-corrected significant interactions	0 (0%)
Sample size limitation (adjusted R^2)	-0.018

Note: FDR = False Discovery Rate

5. Conclusion

We investigated the relationships between personality traits, self-perceived distractions, and programming performance among 32 undergraduate Information Systems students. Our analysis integrated comprehensive IDE interaction data with academic outcomes to examine how individual differences influence programming success and learning behaviors in introductory programming courses.

Answering RQ1: Our analysis revealed predominantly weak and non-significant associations between the Big Five personality traits and self-perceived distractions. Among the traits, only agreeableness and conscientiousness exhibited a significant positive correlation. We observed no significant relationships between either internal or external distractions and any of the individual personality dimensions. These findings contradict previous research that has shown strong associations, particularly between neuroticism and susceptibility to distraction [Seddigh et al. 2016, Eysenck and Graydon 1989].

Answering RQ2: Our analysis demonstrated that internal distractions were significantly associated with reduced programming performance, with notable reductions in successful submissions, success rates, and code correctness, supporting cognitive load theory predictions [Paas and Van Merrienboer 2020]. Among personality traits, conscientiousness emerged as the strongest predictor of academic success, showing significant correlations with exam 3 performance and overall GPA, aligning with established meta-analytic findings [Mammadov 2022, Zell and Lesick 2022]. Early IDE behavioral metrics exhibited strong predictive relationships with subsequent academic performance, with successful submissions demonstrating very high correlations with exam 3 and GPA. Our comprehensive moderation analysis of 190 personality-distraction interactions found no effects that survived FDR for multiple testing, indicating that personality traits do not significantly moderate the relationship between distractions and programming outcomes in our sample.

Based on our results, while conscientiousness could be used to predict academic success and internal distractions were associated with reduced programming performance, we found no evidence for personality-based moderation of distraction effects after appropriate statistical correction. In addition, concerning IDE variables, we found that early IDE behavioral patterns serve as reliable predictors for identifying at-risk students and future academic performance.

5.1. Limitations and Future Research

Our limited sample size resulted in reduced statistical power and yielded negative adjusted R^2 values (-0.018), which raises doubts about the validity of the model. Most critically, our moderation analysis revealed that none of the 14 initially significant personality-distraction interactions survived FDR for multiple testing.

This finding underscores the importance of appropriate statistical correction in exploratory research and suggests that apparent moderation effects in our data are likely false positives. The discrepancy between uncorrected (14 significant) and corrected (0 significant) results demonstrates how multiple testing can severely inflate Type I error rates in complex analyses.

Our reliance on self-reported measures of distraction and the use of the Mini-IPIP version instead of the original Big Five may have led to bias, potentially accounting for the weak correlations we observed with personality. Our study focused on Information Systems students learning C programming at a single institution, which may limit the applicability of our results to other contexts.

Therefore, future studies should involve larger samples from multiple institutions to achieve adequate statistical power for detecting true moderation effects while controlling for multiple testing. Researchers should utilize more objective measures for distraction, such as physiological indicators (e.g., eye-tracking, galvanic skin response), behavioral observations (e.g., off-task behavior tracking), or automated logging of external stimuli.

6. Use of AI

The authors acknowledge the use of ChatGPT for writing assistance, editing, and grammar checking. All ideas, analyses, and conclusions remain our original work, and we take full responsibility for the content's accuracy.

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