Uma investigação empírica da relação entre traços de personalidade, distrações autopercebidas e desempenho em aulas introdutórias de programação

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Universidade Federal de Uberlândia
Faculdade de Computação
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Uberlândia
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Área de concentração: Ciência da Computação

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Coorientador: Prof. Dr. Cleon Xavier Pereira Júnior

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"Everybody in this country should learn to program a computer, because it teaches you how to think."

(Steve Jobs)

Resumo

As aulas introdutórias de programação (IPC, do inglês *Introductory Programming Classes*) têm apresentado altas taxas de reprovação (tipicamente entre 30% e 50%). Portanto, é fundamental compreender quais fatores não cognitivos contribuem para esse alto índice de reprovação. Para investigar essa questão, conduzimos um estudo empírico com o objetivo de analisar as relações entre os traços de personalidade do modelo *Big Five*, as distrações percebidas em sala de aula e o desempenho dos estudantes em aulas introdutórias de programação, considerando duas turmas de alunos do curso de sistemas de informação, sendo 32 estudantes de cada turma, totalizando 64 participantes. Os dados foram coletados por meio de dois questionários: Mini-IPIP para personalidade e um personalizado sobre distrações. Além disso, coletamos registros detalhados do ambiente de desenvolvimento integrado (*Integrated Development Environment* – IDE) CodeBench. Os resultados indicaram que fatores referentes ao sucesso na disciplina dependem, em geral, do contexto. Especificamente, para os estudantes da turma 1, distrações internas impactaram negativamente os indicadores de desempenho, enquanto o traço de conscienciosidade foi identificado como o principal preditor acadêmico de sucesso para esses alunos. Por outro lado, para os estudantes da turma 2, os fatores de personalidade foram os preditores mais dominantes do sucesso inicial. Nesse grupo, a abertura à experiência foi o único fator significativo na previsão de sucesso no início do curso. Além disso, independentemente da turma, constatamos que os indicadores iniciais de desempenho acadêmico obtidos a partir do uso do IDE CodeBench (por exemplo, número de submissões bem-sucedidas e tempo gasto digitando) foram fortes preditores do desempenho acadêmico final. A submissão bem-sucedida de código mostrou-se um indicador confiável de sucesso acadêmico para os alunos da turma 1, enquanto o tempo gasto digitando foi um indicador confiável de sucesso acadêmico para os alunos da turma 2. Por meio de uma correção rigorosa para múltiplos testes, não encontramos evidências que sustentem a ideia de que o efeito das distrações varia de acordo com o perfil de personalidade do indivíduo. Em outras palavras, para o estudo em questão, os traços de personalidade não moderaram o efeito das distrações. Esses resultados sugerem que o desenvolvimento de intervenções educacionais deve levar em consideração a experiência específica de cada grupo de estudantes (iniciantes ou repetentes), em vez de adotar estratégias universais.

Palavras-chave: Programação Introdutória, Traços de Personalidade, Distrações em Sala de Aula.

An Empirical Investigation into the Relationship Between Personality Traits, Self-Perceived Distractions, and Performance in Introductory Programming Classes

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Reuniu-se por videoconferência, a Banca Examinadora, designada pelo Colegiado do Programa de Pós-graduação em Ciência da Computação, assim composta: Professores Doutores: Cleon Xavier Pereira Júnior (Coorientador) - IFGoiano, Fabiano Azevedo Dorça - FACOM/UFU, Filipe Dwan Pereira - UFRR e Rafael Dias Araújo - FACOM/UFU, orientador do(a) candidato(a).

Os examinadores participaram desde as seguintes localidades: Cleon Xavier Pereira Júnior - Iporá/GO, Filipe Dwan Pereira - Boa Vista/RR. Os outros membros da banca e o aluno participaram da cidade de Uberlândia.

Iniciando os trabalhos o presidente da mesa, Prof. Dr. Rafael Dias Araújo, apresentou a Comissão Examinadora e o(á) candidato(a), agradeceu a presença do público, e concedeu ao(á) Discente a palavra para a exposição do seu trabalho

A seguir o senhor presidente concedeu a palavra, pela ordem sucessivamente, aos examinadores, que passaram a arguir o(á) candidato(a). Ultimada a arguição, que se desenvolveu dentro dos termos regimentais, a Banca, em sessão secreta, atribuiu o resultado final, considerando o candidato(a):

Aprovado

Esta defesa faz parte dos requisitos necessários à obtenção do título de Mestre.

O competente diploma será expedido após cumprimento dos demais requisitos, conforme as normas do Programa, a legislação pertinente e a regulamentação interna da UFU.

Nada mais havendo a tratar foram encerrados os trabalhos. Foi lavrada a presente ata que após lida e achada conforme foi assinada pela Banca Examinadora.

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Abstract

Introductory Programming Classes (IPC) have shown high failure rates (typically between 30% and 50%). Therefore, it is essential to understand which non-cognitive factors contribute to this high failure rate. To investigate this issue, we conducted an empirical study aiming to analyze the relationships between the Big Five personality traits, perceived classroom distractions, and student performance in introductory programming classes, considering two groups of information systems students, with 32 students in each group, totaling 64 participants. Data were collected through two questionnaires: Mini-IPIP for personality and a customized one for distractions. In addition, we collected detailed logs from the CodeBench Integrated Development Environment (IDE). The results indicated that factors related to success in the course generally depend on the context. Specifically, for students in group 1, internal distractions negatively impacted performance indicators, while the conscientiousness trait was identified as the main academic predictor of success for these students. On the other hand, for students in group 2, personality factors were the most dominant predictors of initial success. In this group, openness to experience was the only significant factor in predicting early success in the course. Furthermore, regardless of the group, we found that initial academic performance indicators obtained from the use of the CodeBench IDE (e.g., number of successful submissions and time spent typing) were strong predictors of final academic performance. Successful code submission proved to be a reliable indicator of academic success for students in group 1, while time spent typing was a reliable indicator for students in group 2. Through a rigorous correction for multiple testing, we found no evidence supporting the idea that the effect of distractions varies according to an individual's personality profile. In other words, for the study in question, personality traits did not moderate the effect of distractions. These results suggest that the development of educational interventions should take into account the specific experience of each group of students (novice or repeaters), rather than adopting universal strategies.

Keywords: Introductory Programming, Personality Traits, Classroom Distractions.

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Acronyms list

ANOVA Analysis of Variance

CAAE Certificado de Apresentação de Apreciação Ética

CLPM Cross-Lagged Panel Model

CLT Cognitive Load Theory

CS1 Computer Science 1

CSV Comma-Separated Values

FDR False Discovery Rate

fMRI Functional Magnetic Resonance Imaging

FoMO Fear of Missing Out

GPA Grade Point Average

IDE Integrated Development Environment

IPC Introductory Programming Classes

JSON JavaScript Object Notation

LA Learning Analytics

LIME Local Interpretable Model-agnostic Explanations

LMS Learning Management System

LSTM Long Short-Term Memory

ML Machine Learning

MLP Multi-Layer Perceptron

MOOC Massive Open Online Course

MSCS Multi-dimensional Self-Control Scale

NEPS National Educational Panel Study

OJ Online Judge

OLS Ordinary Least Squares

PCA Principal Component Analysis

RI-CLPM Random Intercept Cross-Lagged Panel Model

RNN Recurrent Neural Network

SD Self-Directedness

SEM Structural Equation Modelling

SHAP SHapley Additive exPlanations

SNS Social Networking Sites

SRL Self-Regulated Learning

TIPI Ten-Item Personality Inventory

UFAM Federal University of Amazonas

UUID Universally Unique Identifier

WPGA Web Programming Grading Assistant

Contents

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Thyago Luis Borges e Silva

Chapter 1

Introduction

Introductory Programming Classes (IPC) are foundational courses in computer science education that introduce novice undergraduate students to programming while developing essential problem-solving and critical thinking capacities (MEHMOOD et al., 2020). Despite their significance, these courses are known for elevated failure rates of 30 to 50% (MARGULIEUX; MORRISON; DECKER, 2020; MEHMOOD et al., 2020). Students confront multiple obstacles, including the intricacy of the subject, such as grasping new concepts and programming syntax, besides the cognitive challenges of heightened working memory and attention requirements (MEHMOOD et al., 2020).

Beyond the complex task of learning to program, novice students must also deal with various environmental and internal factors that obstruct the learning process. Several of these factors are classroom interruptions. Both digital and non-digital interruptions have become more pervasive in higher education and can hamper engagement and learning (BRADY; KIM; CUTSHALL, 2021; FLANIGAN; BABCHUK, 2022). While cognitive proficiency has traditionally been the principal variable in educational performance discussions, accumulating evidence reveals that non-cognitive variables, including personality attributes and the aptitude to manage interruptions, are prominent factors for student success (BRANDT et al., 2020; MEHMOOD et al., 2020).

Comprehending how individual differences shape programming performance in introductory programming courses necessitates analyzing both relatively stable personality characteristics and situational obstacles students experience. The Five-Factor Model of personality traits, which categorizes traits under openness, conscientiousness, extroversion, agreeableness, and neuroticism, provides a framework for examining how trait-level individual differences interact to diminish or amplify student academic achievement (DONNELLAN et al., 2006; MAMMADOV, 2022). Studies consistently identify conscientiousness as the personality trait most associated with academic achievement (MAMMADOV, 2022), whereas other traits tend to have more context-dependent associations. However, how these personality traits correspond to students' vulnerability to and management of interruptions in cognitively demanding tasks, such as programming, remains ambiguous.

Interruptions can be classified as internal or external. External interruptions originate from the student's learning environment and typically encompass technological sources such as laptops, smartphones, and social media, as well as noise and other people (BRADY; KIM; CUTSHALL, 2021; DONTRE, 2021; DENG; ZHOU; BROADBENT, 2024). Internal interruptions originate within the individual and include boredom, anxiety, frustration, mind-wandering, fatigue, and socializing during class (BRADY; KIM; CUTSHALL, 2021). Cognitive Load Theory (CLT) indicates that interruptions add extraneous cognitive load to working memory and reduce the working memory storage capacity for new concepts (CHANDLER; SWELLER, 1991; PAAS; VAN MERRIENBOER, 2020). Attention theories reinforce the idea that sustained and selective attention are finite resources for which interruptions compete (DRIVER, 2001; ESTERMAN; ROTHLEIN, 2019).

Personality traits may shape both the perception of interruptions and the strategies for managing them. Individuals low in openness to experience have been demonstrated to be more susceptible to inattentional blindness (KREITZ et al., 2015). Lower conscientiousness has been linked with experiencing greater benefit from using software to block online interruptions (MARK; CZERWINSKI; IQBAL, 2018). Individuals high in anxiety traits (especially neurotic introverts) are more sensitive to interference (EYSENCK, 1991). More broadly, test anxiety makes individuals vulnerable to distraction from threat-relevant information under evaluative stress (KEOGH; FRENCH, 2001). Overall, the findings collectively support the interpretation that personality constructs moderate the way interruptions are interpreted, experienced, and ultimately managed.

Modern Integrated Development Environment (IDE) offers opportunities to investigate the learning process in programming education. By capturing behavioral data such as keystrokes, code submissions, compilation attempts, and attention patterns, IDE provides fine-grained, objective data on student engagement in programming contexts (PEREIRA; FONSECA; OLIVEIRA; OLIVEIRA, et al., 2020; VILLAMOR, 2020). Through IDE log analysis, researchers can investigate the processes involved in learning programming over time, advancing beyond summative assessments toward a more complete understanding of early behaviors that might forecast later success, difficulty, or disengagement. Metrics such as code submission frequency, submission accuracy, error quotients, and temporal coding patterns have proven useful for identifying at-risk students and assessing IDE engagement behaviors related to programming performance (PEREIRA; FONSECA; OLIVEIRA; CRISTEA, et al., 2021; LLANOS; BUCHELI; RESTREPO-CALLE, 2023).

This study investigates the relationships between personality traits, self-perceived interruptions, and programming performance in introductory programming courses. Personality traits and interruption experiences are explored through questionnaire data, while academic outcomes and IDE engagement are examined through log data. The goal is to explore how individual differences shape programming behavior and performance in relation to interruption vulnerability. This investigation contrasts two distinct student populations: first-time learners and repeating students. This comparison ascertains whether the relationships outlined above differ based on prior course experience, as repeating students may have different motivational states, prior content exposure, and increased anxiety about repeated failure.

1.1 Research goals, questions, and challenges

1.1.1 Research goals

The primary objective of this study is to examine the impact of personality traits and classroom disruptions on programming performance in introductory programming courses. To achieve this goal, the following specific objectives were defined:

- To analyze the relationships between the Big Five personality traits, students' self-perceived classroom distractions (both internal and external), and programming performance.
- To investigate whether these relationships differ between two distinct cohorts: first-time introductory programming students (novices) and students repeating the course.
- To identify which personality traits and distraction types act as predictors for programming behaviors and for academic outcomes.
- To determine if early behavioral metrics from the CodeBench IDE are predictors of subsequent, final academic performance.
- To test whether Big Five personality traits moderate the relationship between self-perceived distractions and programming performance outcomes.

1.1.2 Research questions

- **RQ1:** How do personality traits and self-reported distractions relate to programming behavior in introductory programming courses?
- **RQ2:** How do personality traits and distractions predict academic performance?
- **RQ3:** Can early IDE metrics predict subsequent academic performance?
- **RQ4:** Do personality traits moderate the relationship between distractions and programming outcomes?
- **RQ5:** How does prior learning experience influence the relationships between personality, distractions, and programming performance?

1.1.3 Research challenges

- To gather a reasonable amount of data from students.
- To make students adhere to the use of CodeBench instead of CodeBlocks or similar IDEs and make these same students respond to the questionnaires so we could merge the data.
- To generate meaningful features from CodeBench raw data.

1.2 Contributions

- **Context-Dependent Analysis:** We provide evidence that the factors contributing to success in introductory programming are dependent on the student's prior experience (novice vs. repeater), allowing instructors to develop a better learning environment.
- **Identification of Specific Predictors:** Our work identifies the traits and variables to be used as predictors of academic success in the context of introductory programming courses and how they differ based on different types of students and their prior experiences.
- **Validation of IDE Metrics:** Our study confirms that early academic performance indicators gathered from the CodeBench IDE (such as the number of successful submissions for novices and time spent typing for repeaters) are predictors of final academic performance.
- **Guidance for Educational Interventions:** The findings suggest that educational interventions should be tailored to the specific student group (novice or repeater) rather than applying universal strategies, offering a more focused approach to improving failure rates in these courses.
- **Alignment with SDG 4 (Quality Education):** This work addresses the UN's Sustainable Development Goal 4 by tackling high failure rates in tertiary education. By providing an evidence-based framework for tailored interventions, the research promotes a more inclusive, equitable, and quality learning environment in foundational technology courses.

1.3 Dissertation outline

- **Chapter 2 (Theoretical Framework):** Provides the theoretical framework for the study, describing classroom distractions, cognitive load theory (CLT), attention theories, the five-factor model of personality, and the cognitive processes used when learning to program.

- **Chapter 3 (Literature Review):** Describes a literature review covering the works of other researchers who have studied distractions, personality, personality as a moderator, and learning analytics in programming education and other subjects.
- **Chapter 4 (Methodology):** Outlines the research design, participant demographics, ethics considerations, data collection tools (Mini-IPIP, distraction survey, CodeBench IDE), and data processing and statistical analysis techniques.
- **Chapter 5 (Results):** Describes the results of the statistical analyses (Spearman correlations and multiple regression) performed on the data collected and provides explanations of the relationships among the variables and predictive models for Class 1 (novice students) and Class 2 (repeater students).
- **Chapter 6 (Conclusion):** Summarizes the primary elements of the study, details the findings that support the answers to the research questions, identifies potential limitations of the study, and lists all the publications that resulted from this work.

Chapter 2

Fundamentals

Computer science programs typically use IPC as a foundational step for novice undergraduate students with little programming knowledge (MEHMOOD et al., 2020). Numerous undergraduate programs include IPC, enabling students to develop essential skills such as problem-solving and critical thinking (MEHMOOD et al., 2020). These skills are important in today's world (MARGULIEUX; MORRISON; DECKER, 2020).

IPC present significant challenges for novice learners. Many students begin the course without prior experience in abstract thinking or complex problem-solving procedures required for programming tasks (MARGULIEUX; MORRISON; DECKER, 2020; MEHMOOD et al., 2020). As a result, these courses have consistently high dropout and failure rates. Rates can reach as high as 30-50% (MARGULIEUX; MORRISON; DECKER, 2020; MEHMOOD et al., 2020). The challenges students encounter are multifaceted. They range from the complexity of programming concepts and language syntax to the cognitive load imposed on them (MEHMOOD et al., 2020).

Alongside the inherent challenges of programming, students encounter additional obstacles that affect their academic performance. Much research has explored the various factors that influence academic success, which is essential for students' future endeavors (MAMMADOV, 2022). While cognitive ability is the most frequently used predictor of academic success (BRANDT et al., 2020), evidence indicates that non-cognitive factors also play a role (BRANDT et al., 2020; MAMMADOV, 2022). Among these non-cognitive factors, distractions have appeared as a key issue in college classrooms. They can impact students' learning and engagement (BRADY; KIM; CUTSHALL, 2021). Digital distractions, in particular, are prevalent and may hinder student learning (FLANIGAN; BABCHUK, 2022).

Given the challenges students face in IPC classes, it is important to understand them deeply. Understanding the factors that impact student success can help mitigate them. This can improve student engagement, performance, and persistence in the course. This chapter aims to provide a theoretical background for investigating such factors.

2.1 Distractions and Their Impact on Learning

In higher education, most students will encounter distractions within their learning environment. These distractions can impact their learning and engagement with academic tasks (BRANDT et al., 2020; DENG; ZHOU; BROADBENT, 2024). Therefore, it is essential to understand the nature of these distractions and their potential influence on complex learning tasks such as programming.

2.1.1 Definition and Categories of Distractions

Internal and external distractions are common categories of distractions. External distractions originate from the student's environment. The most common are technological distractions, including laptops, smartphones, and social media use, which often lead to multitasking (DONTRE, 2021; DENG; ZHOU; BROADBENT, 2024). Other common external distractions students face include noise and the presence of other people (BRADY; KIM; CUTSHALL, 2021). Deng, Zhou, and Broadbent (2024) further specify external factors related to physical, social, and technological contexts.

Conversely, internal distractions come from within the individual. Boredom, anxiety, frustration, mind-wandering, engaging in social interactions during class, exhaustion, and other factors are all internal distractions (BRADY; KIM; CUTSHALL, 2021). Mind-wandering, in particular, is one of the most common internal distractions that can disrupt students' ability to maintain sustained attention (ESTERMAN; ROTHLEIN, 2019). Researchers also describe internal distractions as those arising from cognitive, emotional, and behavioral conditions (DENG; ZHOU; BROADBENT, 2024).

Having established these forms of distraction, it is essential to examine the underlying mechanisms that affect student learning. The CLT principles provide insights into how these defined distractions influence cognitive processing and knowledge acquisition.

2.1.2 Cognitive Load Theory and Distractions

CLT provides a framework (Figure 1) for understanding how distractions impact learning. According to CLT, human working memory is limited in its ability to process new information (PAAS; VAN MERRIENBOER, 2020). Learning new things requires cognitive resources directed toward activities linked to the learning task rather than unrelated or irrelevant processes (CHANDLER; SWELLER, 1991).

According to Paas and Van Merrienboer (2020), distractions can be considered a source of extraneous cognitive load. This is not inherent to the learning material but is imposed by how it is presented. When students are distracted, their cognitive resources are divided between the task and the distraction. This consumes working memory capacity that could be dedicated to understanding new concepts (CHANDLER; SWELLER, 1991).

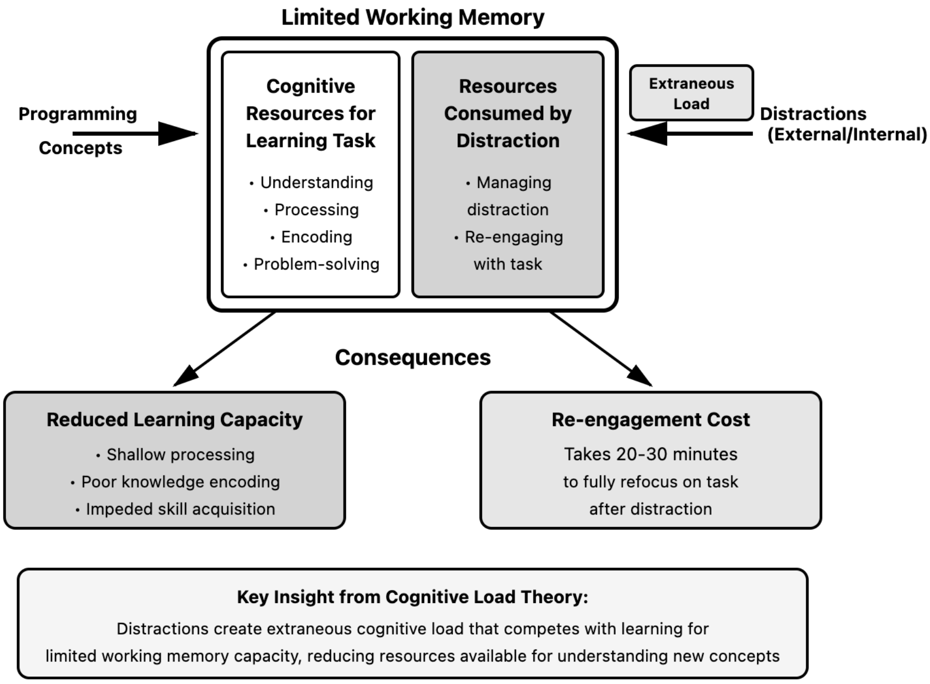

Figure 1 – Visual representation of how distractions create extraneous cognitive load by consuming limited working memory capacity that would otherwise be dedicated to learning tasks. The divided attention results in reduced learning capacity and requires 20-30 minutes for full re-engagement with the task.

This can generate a cognitive load, impeding skill acquisition. In addition, the effort spent on managing distractions and re-engaging with the task can take up to 30 minutes (DONTRE, 2021).

Distractions can impose an extraneous cognitive load that can overwhelm the limited capacity of working memory. However, it is also important to consider how these interruptions compete for attention, another cognitive resource. Attention theories examine the mechanisms by which distractions disrupt the focus required for learning. They emphasize the importance of sustained and selective attention.

2.1.3 Attention Theories and Distractions

According to attention theories, sustained and selective attention are different types of attention that are important for learning. In addition, it is a finite resource, which distractions compete for. Selective attention allows the task at hand to be the dominant stimulus. What a person is aware of depends most on what this person chooses to attend to, not merely all sensory input (DRIVER, 2001).

On the other hand, sustained attention refers to the ability to focus on a single task over time. This is crucial for most everyday tasks, including academic ones (ESTERMAN; ROTHLEIN, 2019). Due to neurocognitive factors, attention is not constant but fluctuates (ESTERMAN; ROTHLEIN, 2019). Internal or external distractions, such as mind-wandering, can divert individuals away from the optimal state of sustained attention. As a consequence, the unattended stimuli do not enter awareness or memory as effectively as they should. This results in shallower learning (DONTRE, 2021).

2.1.4 Distractions in Educational Settings

The body of research often highlights the prevalence and negative impact of distractions in educational settings. Digital distractions are a particular concern. Mobile phone use during classes is frequent and often for off-task purposes, a behavior that hinders learning (FLANIGAN; BABCHUK, 2022). Studies that have identified digital distraction as a problem have shown that 70 to 90% of students text during class (FLANIGAN; BABCHUK, 2022). The off-task use of mobile phones during class increases as the class period progresses. It is linked to diminished learning, poorer note-taking, lower exam performance, and lower Grade Point Average (GPA) (FLANIGAN; BABCHUK, 2022; DONTRE, 2021). Additionally, the detrimental effects of distractions are not limited to distracted individuals but also affect their peers, who can be distracted by them (FLANIGAN; BABCHUK, 2022).

Multitasking is one of the most problematic types of distractions in the classroom. It is negatively related to attention, learning, and academic performance (BRADY; KIM; CUTSHALL, 2021). Multitasking can lead to task abandonment, reducing the student's engagement with the task and increasing the risk of non-completion. Another common distraction in the classroom is the Fear of Missing Out (FoMO), often associated with smartphone use. This can increase distractibility and lead to superficial learning (DONTRE, 2021).

While existing research demonstrates the pervasive nature and detrimental effects of distractions on student learning and academic outcomes, it often focuses on external factors and general trends. It does not examine the specific impact of distractions on individual students. Exploring individual differences, such as personality traits, is beneficial for understanding why some students might be more susceptible to these distractions or better equipped to manage them.

2.2 Personality Traits and Their Role in Academic Contexts

The influence of cognitive factors on academic performance is well established. However, personality traits have also been studied as non-cognitive factors to understand their influence on academic performance (MAMMADOV, 2022). Personality traits are relatively stable patterns of thoughts, feelings, and behaviors. Understanding these traits can provide insights into why students differ in their approaches to learning, their ability to cope with academic stressors, and, ultimately, their success. To understand the relationship between personality traits and various variables, it is essential to measure the values of these traits. The Big Five assessment is among the most frequently used methods. While automatic assessment approaches—such as those leveraging behavioral patterns or linguistic analysis—were initially explored for this study, they were not adopted due to limitations in time and available resources. Instead, the current research utilizes the Mini-IPIP, a self-report measure of the Big Five personality factors (DONNELLAN et al., 2006).

2.2.1 The Five-Factor Model and Academic Performance

The Big Five model proposes that a person's personality can be described using five dimensions. Those dimensions are openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (DONNELLAN et al., 2006; MAMMADOV, 2022; ZELL; LESICK, 2022). Figure 2 illustrates the findings from the literature regarding personality traits and academic performance.

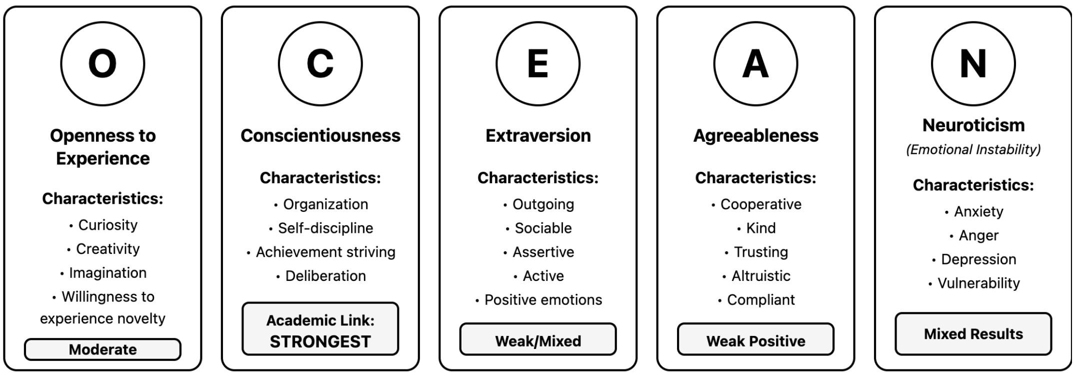

Figure 2 – The Big Five personality traits and their relationships with academic performance according to literature.

Openness to experience is related to curiosity, creativity, imagination, and a willingness to experience novelty (MAMMADOV, 2022; POLLAK et al., 2020; ZELL; LESICK, 2022; RUSSO; MASEGOSA; STOL, 2022). Individuals with higher openness to experience may be more willing to engage with complex ideas and unconventional problem-solving approaches (ZELL; LESICK, 2022). Researchers have found that openness to experience is positively associated with academic performance, although the correlation can vary depending on the educational level. It tends to be higher in the earlier years of education (MAMMADOV, 2022; ZELL; LESICK, 2022). For instance, a study of a first-year class in

Italy revealed a link between openness to experience and GPA (CORAZZINI et al., 2021). Additionally, in the context of a robot programming course, this trait was identified as a negative predictor of primary stress appraisal. This indicates that students with higher openness to experience perceived or experienced tasks as less stressful (POLLAK et al., 2020).

Conscientiousness is related to organization, self-discipline, achievement striving, and deliberation (POLLAK et al., 2020; ZELL; LESICK, 2022; RUSSO; MASEGOSA; STOL, 2022). Conscientious students tend to plan more effectively and carry out their tasks more efficiently (MAMMADOV, 2022). Among all Big Five factors, conscientiousness is the most consistent predictor of academic performance across various studies and meta-analyses (MAMMADOV, 2022; CORAZZINI et al., 2021; ZELL; LESICK, 2022). Perfectionism, which is a facet of conscientiousness, also correlates with academic performance (MATEUS et al., 2021). In contrast to high openness to experience, conscientious students might initially perceive programming tasks as more stressful due to their higher personal standards. However, they were found to have a higher disposition toward the focused effort required by programming (RUSSO; MASEGOSA; STOL, 2022).

Extraversion relates to an individual's tendency to be outgoing, sociable, assertive, and more active. It also relates to experiencing positive emotions, often seeking stimulation and the company of others (MAMMADOV, 2022; POLLAK et al., 2020; ZELL; LESICK, 2022; RUSSO; MASEGOSA; STOL, 2022). According to some meta-analyses, the relationship between academic performance and the extraversion trait is mixed. It shows near-zero or slightly negative associations (MAMMADOV, 2022). This suggests that more extroverted students may not experience significant challenges in achieving good grades compared to their peers. However, introverted students may handle the solitary nature of some programming tasks more effectively (RUSSO; MASEGOSA; STOL, 2022).

The trait that reflects an individual's interpersonal tendencies is known as agreeableness. More agreeable individuals tend to be more cooperative, kind, trusting, altruistic, and compliant (MAMMADOV, 2022; POLLAK et al., 2020; ZELL; LESICK, 2022; RUSSO; MASEGOSA; STOL, 2022). Agreeableness often shows a weak positive association with academic performance (MAMMADOV, 2022; ZELL; LESICK, 2022). This means that agreeable individuals might have fewer social conflicts and receive more support, which can indirectly aid academic pursuits (POLLAK et al., 2020). However, as with extraversion, it does not appear to significantly impact students' performance.

Neuroticism, which is characterized by low emotional stability, indicates a tendency to experience negative emotions such as anxiety, anger, depression, and vulnerability (MAMMADOV, 2022). While neuroticism appears to be detrimental for students, studies reveal a mixed correlation between this trait and academic performance (MAMMADOV, 2022; ZELL; LESICK, 2022). However, high neuroticism can lead to stress and anxiety, which can impair performance (MAMMADOV, 2022). This suggests that individuals less prone to negative emotions may be better equipped to handle the frustrations and complexities inherent in learning to program.

In conclusion, personality traits have been found to have a relationship with academic performance. This is particularly true for those outlined in the Five-Factor Model. Conscientiousness emerges as a consistent predictor of academic achievement. There were also positive associations between openness and academic performance, especially for tasks that require intellective or cognitive stimulation. It is also likely that extraversion, agreeableness, and neuroticism play a more conditional part in their relationships with academic performance. However, these personality traits are still part of a student's psychological profile. In the learning context of introductory programming, extraversion, agreeableness, and neuroticism may negatively impact learning performance.

2.3 Personality as a Moderator of Distraction Perception and Management

Distraction and personality have been discussed separately throughout earlier sections, but their interplay has not been addressed. This section discusses the moderation a personality trait can have on an individual's distraction management and how they respond to environmental stimuli.

2.3.1 Susceptibility to and Perception of Distractions

The ease with which individuals are distracted and their perception of these distractions have been linked to specific personality dimensions. For instance, individuals with low scores of openness to experience have been shown to be more susceptible to inattentional blindness. This means they do not perceive unexpected objects when their attention is engaged elsewhere (KREITZ et al., 2015). This suggests that lower openness might be linked with a narrowly focused attention style. Conversely, individuals scoring high in openness may have a more fluid structure of consciousness. This makes them more receptive to unexpected stimuli and less prone to inattentional blindness (KREITZ et al., 2015).

Conscientiousness, another personality dimension, also appears to modulate the effects of distraction. It was found that individuals lower in conscientiousness reported greater benefits in focus and productivity when software to block online workplace distractions was used (MARK; CZERWINSKI; IQBAL, 2018). This suggests that these individuals might benefit more from external management strategies for workplace distractions than others (MARK; CZERWINSKI; IQBAL, 2018). Although it was marginally significant, Seddigh et al. (2016) reported that more conscientious individuals in flex offices tended to report higher levels of distractions.

Individuals with emotional stability, which is the inverse of neuroticism, seem to report lower levels of self-rated distractions (SEDDIGH et al., 2016). On the other hand, individuals with high anxiety traits, such as neurotic introverts, were found to be more negatively impacted by distractions (EYSENCK, 1991). Eysenck (1991) suggested that high anxiety reduces an individual's ability to maintain focused attention. This is associated with a higher-than-usual score on the neuroticism trait. Specifically, test anxiety, a situation-specific trait, predisposes individuals to become distracted by threat-related material. This occurs particularly when under evaluative stress and attempting to use focused attention (KEOGH; FRENCH, 2001). This highlights that for anxious individuals, distraction is often amplified by the emotional significance (e.g., threat) and the specific context (e.g., stress, task similarity) of the distractor (KEOGH; FRENCH, 2001).

Another personality trait that has also been linked to perceived distraction is agreeableness. More agreeable individuals reported experiencing more distractions in open-plan offices compared to those in cell offices (SEDDIGH et al., 2016). Studies (KREITZ et al., 2015) have found that individuals who are more absorbed in what they are doing may be more likely to miss things they are not paying attention to. This suggests that they are focused enough to filter out other information effectively. However, the nature of the task appears to moderate this relationship.

2.3.2 Personality and Distraction Management

Personality traits not only affect the perception of distractions but also the strategies individuals use—or fail to use—to manage them. Individuals high in conscientiousness and self-control may already possess effective self-regulation techniques. Mark, Czerwinski, and Iqbal (2018) found that this group did not report an enhanced sense of control when distractions were blocked. In fact, they experienced a higher workload. This could be because they typically utilize online distractions for necessary micro-breaks. Removing these without providing alternatives led them to work for longer, more demanding periods (MARK; CZERWINSKI; IQBAL, 2018). Some with greater self-control even perceived distraction-blocking software as overly controlling or unnecessary (MARK; CZERWINSKI; IQBAL, 2018). In contrast, those lower in self-control found such external management tools beneficial. They often expressed a desire to develop better personal strategies for managing distractions (MARK; CZERWINSKI; IQBAL, 2018).

The trait of agreeableness might influence distraction management through interpersonal dynamics (SEDDIGH et al., 2016). Seddigh et al. (2016) proposed that agreeable individuals might experience more distractions in shared environments, such as open-plan offices. This occurs because their inclination to maintain social harmony may make them less likely to assert their need for an undisturbed workspace. This reluctance to prioritize personal focus could be seen as a less effective coping strategy in noisy environments (SEDDIGH et al., 2016).

Difficulties in managing specific types of cognitive content are evident in individuals with high test anxiety. Their susceptibility to threat-related distractors, especially under stress, suggests a failure in the cognitive control mechanisms necessary to ignore or suppress such intrusive thoughts and stimuli when attempting to focus on a task (KEOGH; FRENCH, 2001). Similarly, the finding that neurotic introverts (high trait anxiety) are more easily distracted by task-similar stimuli suggests a less effective attentional filtering or management capability compared to stable extroverts (EYSENCK, 1991).

2.3.3 The Moderating Role of Context

The relationship between personality and distraction is shown to be context-dependent. The nature of the distractor itself is a key moderator. For instance, the emotional valence (e.g., threat-related words for test-anxious individuals; (KEOGH; FRENCH, 2001)), physical salience (for those low in Self-Directedness (SD) individuals; (DINICA et al., 2016)), or similarity to the primary task (for neurotic introverts; (EYSENCK, 1991)) can determine whether a particular personality trait leads to heightened distractibility. Research also shows that meaningful word distractors are generally more disruptive than non-word patterns across different individuals (KEOGH; FRENCH, 2001).

The environment or situation is another moderator. The type of office moderated the relationship between three dimensions of personality (emotional stability, agreeableness, and openness) and self-reported distraction (SEDDIGH et al., 2016). Evaluative stressors are central to how distraction vulnerability manifests for individuals with test anxiety (KEOGH; FRENCH, 2001). It follows that the impact of task function and attentional state demands (such as focused attention and selective attention) may be influenced by personality. This in turn may define the extent of distraction. For example, test-anxious individuals were more distracted by threats when a task appeared to engage focused attention (KEOGH; FRENCH, 2001). Furthermore, interventions for distraction management, such as blocking software, demonstrate that personality (and self-control factors) influences outcomes and the perceived impact of this type of intervention (MARK; CZERWINSKI; IQBAL, 2018).

In summary, personality traits serve as moderators for distractions in perceiving, being affected by, and managing them. Different facets of personality influence a person's awareness of the environment, such as the trait of openness. Other facets, like conscientiousness and self-control, contribute to baseline distractibility and an individual's response to external management inputs. Those with anxious personality profiles tend to exhibit greater sensitivity to specific distractions, especially when in similar stress conditions. This suggests a diminished capacity to filter out or manage those distracting inputs. Consideration of other traits, such as SD agreeableness, is also important. SD can affect an individual's susceptibility to salient cues, potentially by influencing how they interact with distractions. Agreeableness may contribute to how someone manages their interpersonal styles in distracting environments.

Understanding how personality traits moderate distraction perception and management underscores the importance of examining individual differences in complex cognitive tasks and learning environments. Such insights have implications for educational settings in disciplines that demand sustained concentration and cognitive effort. Introductory programming courses represent environments where students encounter numerous potential distractions while simultaneously developing new problem-solving and critical-thinking skills. Evaluating how students manage distractions and maintain attention is vital for effectively assessing and facilitating their learning processes. The subsequent sections delve into the metrics and methods often used to define and measure programming performance. They explore behavioral indicators of engagement derived from IDE interactions and examine cognitive processes integral to programming tasks.

2.4 Learning and Behavior in Introductory Programming

IPC are not just learning language syntax. They require the development of problem-solving skills and the application of critical thinking (MEHMOOD et al., 2020). To improve teaching strategies, it is essential to assess students' learning and understanding of their behavior throughout this process. This section discusses how programming performance is defined and measured. It also discusses how IDE data can be used to understand programming behaviors and the cognitive processes underlying programming.

2.4.1 Defining and Measuring Programming Performance in Introductory Courses

Overall grades are usually the most used measure to assess students' performance. However, metrics like the correctness of submitted solutions to programming exercises and task completion rates are also used (LLANOS; BUCHELI; RESTREPO-CALLE, 2023). Another indicator of students' performance is the quality of the code. This includes not only its correctness but also its design and efficiency, which indicates understanding and skill acquisition (SUN; WU; LIU, 2020). Students encounter difficulties grasping core programming concepts. Assessing learning at various cognitive levels for specific concepts is crucial. Traditional assessments focus on the final product, but current research emphasizes the importance of understanding the learning process (VILLAMOR, 2020).

2.4.2 Understanding Programming Behavior through IDE Data (Log Data Analysis)

Once used only for coding, IDE have now been used to collect data. They offer a source for understanding students' learning behaviors in an objective manner. Known as learning analytics or educational data mining, analyzing this type of data enables researchers to move beyond final assessments. It allows them to gain insights into the processes involved in learning to program (PEREIRA; OLIVEIRA, et al., 2020; VILLAMOR, 2020). Using this process-oriented approach, professors examine elements such as students' compilation behaviors and the evolution of their source code to understand their progress and struggles (VILLAMOR, 2020).

Various metrics derived from IDE logs can indicate aspects of student engagement, effort, strategies, and difficulties. The frequency and nature of code submissions and compilations are indicators of code quality (PEREIRA; FONSECA; OLIVEIRA; CRISTEA, et al., 2021). Metrics, such as Jadud's Error Quotient (which provides a signal of student productivity related to student work, as it relates error messages to successful compilations) (PEREIRA; FONSECA; OLIVEIRA; CRISTEA, et al., 2021), the Watwin Score (which counts the time between compilation errors, as well as the compilation errors), and Repeated Error Density can show evidence of patterns of struggle or debugging (VILLAMOR, 2020). Pereira, Fonseca, Oliveira, Cristea, et al. (2021) identified predictors of performance indicators. These included the number of submissions on the last day, the total number of compilation errors, the total number of failed submissions, and the total number of successful submissions. Likewise, Llanos, Bucheli, and Restrepo-Calle (2023) used the number of attempts students made in programming labs to predict performance.

Analyzing when students take action can provide clues to their level of engagement and the pace at which they solve problems. For example, Llanos, Bucheli, and Restrepo-Calle (2023) discussed the "delivery time" of assignments. Other examples of metrics (such as average time between submissions, average time to solve a problem/submission, and average time to complete exercises) are related to reflection, difficulty, or procrastination (PEREIRA; FONSECA; OLIVEIRA; CRISTEA, et al., 2021). Metadata regarding students' work in the IDE can also be revealing. Total time with the IDE, number of copy-pastes, number of deletes, and number of keystrokes can provide evidence of students' editing effort, exploration of solutions, or use of externally generated knowledge (e.g., copying code from an online site or from a friend's code). These metrics align with the use of IDE for collecting metadata regarding "the number of selections" and "the number of types." Other metrics, such as the time students begin and finish their programming, the time between their programming sessions, and the frequency with which students save their work, may reveal evidence of engagement, persistence, or cramming behavior (OMER; FAROOQ; ABID, 2020; MEHMOOD et al., 2020).

Durak and Bulut (2024), Pereira, Fonseca, Oliveira, Cristea, et al. (2021) and Omer, Farooq, and Abid (2021) have leveraged such data to create models that predict student success. They also identify at-risk students and understand novices' learning trajectories. Similarly, cognitive learning analytics frameworks that focus on assessment data and conceptual understanding aim to provide sustainability and efficacy to programming courses (OMER; FAROOQ; ABID, 2020).

2.4.3 Cognitive Processes in Programming

Program comprehension, an aspect of learning to program, is a cognitive process. Peitek et al. (2018) employed Functional Magnetic Resonance Imaging (fMRI) to investigate brain activity during comprehension tasks. They reported that different brain activations in five areas were associated with activity related to working memory, attention, and language processing. Given that programming requires accessing and retaining information (working memory), sustaining attention on the programming task (attention), and understanding a system of symbolic representations (language processing), the activation patterns are understandable. The authors also observed less activity in the default mode network. Default mode brain activity occurs during rest and mind-wandering, indicating that most of their cognitive effort was spent on the programming task (PEITEK et al., 2018). These findings are consistent with programming's demands on cognitive effort, memory resources, attention, and working memory. This is why impairments to working memory and attention (specifically those caused by distractions) are important. These findings regarding the cognitive resources involved in programming may also highlight the significance of cognitive load.

In summary, learning to program is a journey. Students must learn new things, develop skills, behave in new ways, and pay attention to several cognitive processes. By analyzing performance outcomes, IDE interaction, and cognitive effort aspects, a comprehensive understanding of the student learning experience in an introductory programming course can be formed. Comprehending the student learning experience is crucial to developing learning environments, teaching strategies, and interventions.

Chapter 3

Literature Review

This chapter provides a comprehensive review of the literature, laying the groundwork for a more profound understanding of the complex roles that various factors play in student academic engagement and performance. The chapter begins with a review of the extensive literature on distractions, encompassing their various forms and documented effects on cognitive functioning and educational performance. It goes on to draw upon the literature on personality psychology and examines the role of personality traits as factors in academic performance. It also examines the moderating role of personality in relation to distractions, including how individual differences influence sensitivity and reactions to disruptions. Finally, this chapter reviews the field of learning analytics.

3.1 Studies on Distractions

A meta-analysis by Sunday, Adesope, and Maarhuis (2021) put together data from 44 studies, encompassing nearly 148,000 college students across 16 countries, to explore how smartphone use (addiction) impacts academic success. The research found that smartphone addiction is linked to lower college grades, showing a small, negative overall effect on learning with a correlation coefficient (r) of -0.12. Researchers suggest this negative effect is tied to the impairment of necessary cognitive abilities and may increase if students use their phones during study time. Furthermore, the strength of this relationship varied depending on factors like the study's location (continent), the student's primary reason for using the phone, and specific predictors of their GPA.

A study by Braat-Eggen et al. (2021). investigated how open-plan study noise, including background speech and reverberation, affected the cognitive performance and perceived disturbance of sixty-six students across tasks like reading, math, and logical reasoning. While objective test scores for reading comprehension and mental arithmetic remained stable under noisy conditions, performance on the logical reasoning task declined when subjects were exposed to background speech. Furthermore, despite the stability of most objective metrics, students reported feeling highly disturbed by the noise and believed their performance was worse than in the quiet setting, rating the reading comprehension task as the most noise-affected.

Brady, Kim, and Cutshall (2021) looked at what pulls students' attention away from their work and how they handle these distractions from a Self-Regulated Learning (SRL) perspective. They followed 244 students in a "learning to learn" class, using Ecological Momentary Assessment and thematic analysis to sort out different distractions, their causes, and ways students tried to manage them. Distractions fell into five areas: cognition, motivation/affect, behavior, context, and physiology, with physiology mentioned less often in SRL studies. Technology and the learning environment came up most as sources of distraction, while boredom and anxiety were common motivational reasons. Students usually focused on adjusting their surroundings, though their strategies didn't always match the actual cause of the distraction.

Wang et al. (2022) found that college students often struggle with digital distractions during class activities. According to them, to tackle this problem, they emphasized the importance of self-regulated learning (SRL). Reviewing several studies, the authors showed how internet use, social media, and texting can disrupt learning. They examined these distractions through the SRL framework to understand their links to anxiety, low motivation, and fear of missing out. The study suggested that teaching students clear SRL strategies, like Pintrich's four-phase model (2000), could help them maintain focus. By developing skills in goal setting, time and environment management, self-monitoring, and reflection, students can better handle technology use and improve their attention, engagement, learning, and overall performance.

Liao and Wu (2022) examined how digital distractions, peer learning attitudes, and peer learning activity influenced students' performance in a blended statistics course making use of problem-based learning (PBL). The study had a cohort of 51 Taiwanese graduate students and used a multimodal Learning Analytics (LA) model that combined survey responses on student traits, perceived digital distractions, and self-reported peer learning attitudes with objective measures of peer learning from Facebook messages, classified as course-related or unrelated. Higher self-reported digital distraction was linked to lower final grades, while a positive peer learning attitude was linked to better grades. Actual peer learning activity from Facebook was a stronger predictor of performance than perceived peer learning attitude. Prior knowledge also predicted success, whereas more time per Facebook visit and frequent interactions with friends were linked to lower grades.

Flanigan and Babchuk (2022) made use of phenomenology to explore how college instructors perceive and respond to students' digital distractions, such as off-task mobile use in class. Through interviews with 11 instructors, the study examined how these distractions affected teaching methods, decision-making, interactions with students, and job satisfaction. The results showed that teachers often saw students getting distracted and thought it hurt their learning. Most of them thought they were not responsible for dealing with this behavior and would rather make lessons interesting than punish students, since they were afraid that doing so would hurt relationships and not work. The research indicated that student distractions frequently led to teacher frustration and were perceived as detrimental to both the student-teacher relationship and the instructors' professional fulfillment.

Pérez-Juárez, González-Ortega, and Aguiar-Pérez (2023) explored digital distractions among engineering students during laboratory work in 2021-2022. Using surveys and discussions with 105 students and bivariate correlation analysis, the study found that many students felt digital distractions lowered their lab performance, with 69.2% believing they could do better if distractions were reduced. Almost half (47.57%) thought digital distractions had a bigger impact than non-digital ones. Common digital distractions included device notifications (56.12%), social media (43.88%), and messaging (41.84%). Non-digital distractions, such as chatting with peers (50.73%), unclear instructions (48.98%), faulty equipment (52.04%), and lab conditions (63.27%), also affected students. Off-task web browsing was linked to students' feeling they could use lab time more efficiently.

In classroom settings, university students use SRL strategies to handle multitasking caused by distractions (DENG; ZHOU; BROADBENT, 2024). The study surveyed 385 students from three Chinese universities and interviewed 15 more. It found that both internal factors (cognitive, emotional, and behavioral) and external factors (physical, social, and technological) had an influence on multitasking. Students adjusted their behaviors and learning strategies based on their motivation and interest in the material. Some SRL strategies included blocking distracting websites and managing attention, for example, by listening to music. Cell phones were the most common source of distraction.

3.2 Studies on Personality

Brandt et al. (2020) examined how personality (Big Five traits), cognitive ability (fluid intelligence), and academic performance (grades and test scores) related across contexts in a sample of 12,915 German ninth graders from the National Educational Panel Study (NEPS). Using the BFI-10 questionnaire, a matrix test, and multiple group structural equation models, the researchers found that these relationships differed by school subject and ability track. Cognitive ability, emotional stability, and conscientiousness related more to mathematics performance, while openness and extraversion related more to German performance. Cognitive ability and conscientiousness showed stronger correlations with performance in academic tracks than in intermediate or vocational tracks, whereas agreeableness showed a negative correlation in academic tracks. Personality traits had a larger impact on grades in academic tracks than in other tracks. Brandt et al. (2020) concluded that most trait-performance relationships depended on subject, track, or both.

Cárdenas Moren et al. (2020) looked at how personality traits related to academic performance in 235 engineering students at the Pontifical Catholic University of Valparaíso. Using the NEO Five-Factor Inventory to measure personality and cumulative grades to measure performance, the researchers analyzed data through descriptive statistics, correlations, Analysis of Variance (ANOVA), and econometric modeling. Students showed, in general, high neuroticism, low extraversion, medium openness, and low agreeableness and conscientiousness. Initial correlations suggested that lower extraversion and medium openness were linked to better performance, but the final econometric model found that academic performance related negatively to extraversion and openness and positively to conscientiousness.

Negru-Subtirica et al. (2020) studied the link between academic achievement (GPA) and Big Five personality traits in 1,151 Romanian adolescents (average age 16.45) over three points in the school year. Personality was measured with the Big Five Inventory, and GPA scores were verified from school records. The study used Cross-Lagged Panel Model (CLPM) to examine group-level effects and Random Intercept Cross-Lagged Panel Model (RI-CLPM) for within-person changes. Results showed in general that higher GPA influenced personality development more than personality influenced GPA. At the group level, higher GPA related to greater extraversion, agreeableness, and openness, and openness in turn predicted a slight increase in GPA over time. At the individual level, rising GPA linked to lower neuroticism relative to a student's usual level. The authors suggested that GPA has a bigger effect on personality when it signals social standing to peers than when it reflects personal change.

Coenen et al. (2021) verified whether conscientiousness, emotional stability, and risk preference related to academic performance in higher education and whether heterogeneous scale use biased self-reported personality measures. The study included first-year Dutch economics and business students (N = 1,056 for risk preference, 625 for conscientiousness and emotional stability) who completed single-item measures for each trait. Using anchoring vignettes to create corrected personality scores, the researchers compared these with uncorrected scores in predicting performance in an introductory quantitative methods course through regression models. Self-reported conscientiousness showed a positive relationship with performance, but this relationship appeared inflated; the vignette-corrected measure also showed a positive relationship, though smaller. Neither uncorrected nor corrected emotional stability measures related to performance, though uncorrected estimates were larger. After accounting for heterogeneous scale use, the negative correlation between uncorrected risk preference and performance turned nonsignificant, suggesting the relationship was an artifact of scale use. The researchers concluded that subjective personality measures overstated their predictive validity for academic success and that anchoring vignettes offered more accurate measurement.

Corazzini et al. (2021) examined how the Big Five personality traits (extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience) relate to first-year GPAs of 3,242 Italian university students aged 18 to 24 at the University of Messina, who completed the Ten-Item Personality Inventory (TIPI) at entry. Using Ordinary Least Squares (OLS) estimates and controlling for student and parental characteristics, they standardized GPA within each course to account for program differences. The results showed that conscientiousness and openness to experience were linked to higher GPAs: a one standard deviation increase in conscientiousness raised GPA by 9.3% of a standard deviation, and openness by 3.8%. These effects persisted after accounting for school and family background. Female students had slightly higher GPAs, and although there were gender differences in trait scores, the influence of traits on GPA was similar for both genders. Extraversion, agreeableness, and emotional stability showed no clear effect on GPA.

Zell and Lesick (2022) combined 54 meta-analyses covering 2,028 studies with 554,778 participants to examine the link between the Big Five personality traits (extraversion, agreeableness, conscientiousness, neuroticism, and openness) and overall performance. Conscientiousness showed the strongest correlation with performance ($\rho = 0.19$), while the other traits had smaller effects: extraversion and agreeableness ($\rho = 0.10$), neuroticism ($\rho = -0.12$), and openness ($\rho = 0.13$). Correlations varied by type of performance: conscientiousness related more to academic ($\rho = 0.28$) than job performance ($\rho = 0.20$), and extraversion and neuroticism were weaker for academic outcomes ($\rho = -0.01$, $\rho = -0.03$) than for job performance ($\rho = 0.14$, $\rho = -0.15$). Results were consistent across independent meta-analyses.

Mammadov (2022) analyzed 267 samples (N = 413,074) from 228 studies (1990–2020) on Big Five traits and academic performance. Cognitive ability predicted academic performance best. For personality traits, conscientiousness was the strongest predictor (mean corrected $\rho = 0.27$) and added predictive value beyond cognitive ability, explaining 28% of personality-related variance in academic performance. Openness and agreeableness showed correlations of 0.16 and 0.09, while extraversion ($\rho = 0.01$) and neuroticism ($\rho = -0.02$) showed no relationship. Education level affected these patterns: openness, extraversion, and agreeableness related more to performance in elementary and middle school than later years. Asian samples showed larger correlations for all traits compared to samples from other regions.

Meyer et al. (2023) analyzed how the Big Five personality traits relate to student achievement across subjects (language vs. STEM) and types of assessment (grades vs. test scores). They combined 78 studies with 1,491 effect sizes from 110 samples, representing about 500,000 students from elementary to high school. Using a random-effects model with robust variance estimation, they calculated average correlations. The findings showed that subject and assessment type affected the links between personality and performance. Openness was more connected to language, conscientiousness to grades, extraversion to language outcomes, agreeableness to language grades and test scores but not to STEM test scores, and neuroticism had stronger negative associations in STEM and for test scores. The results suggest that both the subject area and the way achievement is measured matter when studying personality and academic performance.

3.3 Studies on Personality as a Moderator of Distractions

Zulfiqar et al. (2023) examined how excessive Social Networking Sites (SNS) use impacts workers' mental performance, considering task distraction as a mediator and personality type as a moderator. They surveyed 248 Pakistani IT workers three times, collecting data on SNS use, distraction, mental performance, and personality, then analyzed it using Structural Equation Modelling (SEM). Results indicated that excessive SNS use directly harmed mental performance, and task distraction both reduced performance and helped explain the link between SNS use and mental ability. Personality type played a role: extroverts showed larger declines from excessive SNS use, while introverts showed larger declines from task distractions. These findings suggest that excessive SNS use damages mental performance, with extroverts more vulnerable to overuse and introverts more vulnerable to distractions.

Nilsen, Bang, and Røysamb (2024) studied how the Big Five traits (measured with the NEO-PI-3) relate to three kinds of self-control: general, inhibitory, and initiatory, using the Multi-dimensional Self-Control Scale (MSCS) in 480 military cadets, paying special attention to neuroticism as a moderator. They found that neuroticism was linked to lower self-control across all types, while extraversion and conscientiousness related to higher self-control. No link was found between openness and agreeableness. When controlling for other traits, sex, and age, neuroticism predicted lower general and inhibitory self-control, conscientiousness predicted higher levels across all types, and extraversion predicted only higher initiatory self-control. Openness and agreeableness showed no unique effects. Neuroticism also made the positive links between extraversion or conscientiousness and both general and inhibitory self-control weaker, especially when tied to negative emotional traits. The study suggests that different kinds of self-control interact with personality in distinct ways, with neuroticism shaping these patterns most clearly.

Emara et al. (2025) examined the interrelations among university students' personality traits, attention levels, and attention control strategies during online learning amid the COVID-19 pandemic. The study found three profiles based on survey data from 400 students. People in the "Self-Attention Regulated" group had fewer problems with attention, used control strategies more, scored higher on conscientiousness and openness, were often older, and studied online for longer. The "Hanging-On" group had normal attention and personality patterns. The "Social Media-Distracted" group was younger, more easily distracted by social media, and had higher scores on neuroticism. The authors posited that understanding these patterns can assist universities in developing distance learning programs that more effectively accommodate students with diverse characteristics and attention modalities.

3.4 Studies on Learning Analytics

Hsiao, Huang, and Murphy (2017) reported on the development and testing of an educational tool, the Web Programming Grading Assistant (WPGA), which used learning analytics to grade paper-based programming assessments in a blended learning course. The goal was to make grading more consistent, provide faster feedback, and understand how students reviewed and reflected on their work. The study included two parts: a lab study comparing a semantic partial credit scoring algorithm with six graders and a classroom study tracking all 232 students' interactions with WPGA during quizzes and an exam. Interaction patterns were analyzed with Hidden Markov Models. Results showed that WPGA's algorithm raised grading accuracy by 20%. Students who accessed WPGA for review generally engaged with the material, and showing the grading process increased participation. Students who used the system more often tended to score higher on the exam. Behavior patterns revealed that A-grade students revisited and corrected mistakes, while B-grade students checked scores repeatedly but did not reflect on errors.

Pereira, Fonseca, Oliveira, Oliveira, et al. (2020) examined how well different deep learning models predict student outcomes in introductory programming courses and explored the use of SHapley Additive exPlanations (SHAP) to link student activity on an Online Judge (OJ) to performance. They analyzed data from 1,082 students using CodeBench OJ, including submissions, errors, solved problems, and time spent as parameters. The models (Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM)) were used to predict pass/fail status at 25%, 50%, 75%, and 100% of the course. The LSTM model generally gave better early predictions than MLP and RNN, even using only the first 25% of course data. SHAP identified key features influencing outcomes, such as "problems solved successfully," "number of runs," "distinct problems attempted," and "time on OJ." Students who solved more problems tended to pass, while frequent unsuccessful runs and few attempted problems were linked to failure. The study proposed that interpretable deep learning can reveal patterns in student behavior connected to course performance.

Moreno-Marcos et al. (2020) looked at factors affecting the accuracy of academic performance predictions in Massive Open Online Course (MOOC)s. They tested how different types of data, such as demographics, interaction with the platform, and assessments, along with the timing of predictions (early, midpoint, or end of the course), influenced results. Using data from 41,766 learners across 10 MOOCs on Coursera and edX, several machine learning models, including logistic regression, random forest, support vector machines, gradient boosting, and neural networks, were trained to predict course completion. Assessment data predicted outcomes best, especially later in the course, while interaction data were more useful early on than demographics. Models using all data types generally performed better. Accuracy improved as students progressed and added more data. No single algorithm always performed best, though tree-based models like Random Forest and Gradient Boosting often scored higher. Other factors, such as platform, course subject, length, and enrollment, had some influence but were not consistent.

Chen et al. (2020) studied how students' learning behaviors affected small improvements in code quality and their performance in a beginner Java programming course. Using log data from 69 undergraduates, they examined submission patterns, including number of attempts, time to start and finish assignments, and time spent on errors like compilation or style failures. They applied K-means clustering with Principal Component Analysis (PCA) to group students by submission behaviors and built a model to predict at-risk students from early assignment engagement. Findings showed that students who started assignments early and submitted frequently tended to get higher grades, especially if they quickly fixed style errors. The study identified five behavior types: "Effective," "High-effort," "Average," "Blind-trial," and "Low-effort" learners. Using features related to submission and code quality, the authors created an early warning model that identified at-risk students with 87% accuracy before the midterm.

Pereira, Oliveira, et al. (2020) investigated how students performed and learned in CS1. They analyzed detailed interaction data from CodeBench, an online judge, to identify helpful and unhelpful programming behaviors. Data from keystrokes, submissions, and grades of 2,058 non-computer science students collected over three years were used. K-means clustering grouped students using 16 behavioral features such as procrastination, code changes, errors, and IDE use. Success in problem-solving and persistence served as evaluation criteria. Three clusters emerged: Effective (Cluster A), Average (Cluster B), and Ineffective (Cluster C). These clusters showed clear differences in behaviors and outcomes. Effective students managed errors, stayed engaged, coded faster, and kept trying, while less effective students made more syntax mistakes and relied more on copying. Association rule mining highlighted behavioral patterns and early signs of struggling students.

Pereira, Fonseca, Oliveira, Cristea, et al. (2021) worked on making black-box models for predicting student performance in introductory programming more understandable. They connected model features to psychological traits like goal orientation, self-efficacy, and personality to see how these relate to success or failure. In a study at a Brazilian university, data was collected from 492 undergraduate students, including their activity on the CodeBench system (submissions, errors, problems solved), survey responses on goal orientation, self-efficacy, and Big Five personality traits, and final grades. A Random Forest model was used to predict performance, and Local Interpretable Model-agnostic Explanations (LIME) and SHAP provided explanations that were linked to psychological concepts. The results showed the model could identify students at risk of failing. Group-level predictors included conscientiousness (e.g., problems attempted, first-try success), self-efficacy (problems solved), and performance-oriented goal setting (more attempts). At the individual level, low self-efficacy and fewer solved problems predicted failure, while high self-efficacy and more solved problems predicted success. The study demonstrated that combining interpretable machine learning with psychological theory can provide meaningful insights into student performance beyond simple prediction.

López-Pernas, Saqr, and Viberg (2021) investigated how university students learned programming, focusing on their learning approaches (deep, surface, or strategic), strategies, and outcomes (grades and self-assessed skill). The research identified distinct learning profiles among 193 Spanish undergraduates taking an introductory programming course using the Approaches to Learning of Students Inventory (ALSI), grades, Moodle activity data, and competence reports. Analysis showed that using deep and strategic learning methods linked positively to better grades and perceived competence, while a surface approach showed a negative relationship. Data on online activity indicated that reviewing lecture and practice materials correlated with improved performance. Cluster analysis revealed three profiles: "High-engagement" students used deep and strategic methods frequently, accessed resources often, and achieved the best results; "Low-engagement" students rarely used any approach or resource and had the worst outcomes; and the "surface-strategic" group displayed moderate use of surface and strategic approaches, selective resource use, and average results. Furthermore, the relationships between learning strategies differed across these profiles, as shown by epistemic network analysis.

Hellings and Haelermans (2022) examined how a learning analytics dashboard influenced 556 first-year students in a Java programming course. The experiment split participants into groups, providing one set with weekly emails and a tool displaying grade predictions and peer comparisons, while the control group received only emails. Analysis of online activity and exam scores revealed that while the dashboard improved performance on coursework like quizzes, it failed to alter overall final exam grades or passing rates. Effectiveness varied by specialization; software engineering students using the tool achieved higher marks, yet game development students saw their scores decline.

Arizmendi et al. (2023) reviewed how digital learning logs, mainly from an Learning Management System (LMS), can predict student outcomes. The paper summarized current methods, discussed ethical issues, and provided a tutorial for building predictive Machine Learning (ML) models. It reviewed *LMS* data analysis research and walked through data preparation, feature engineering, training *ML* models (like logistic regression, *SVM*s, random forests, and neural networks), and model evaluation. The authors summarized how LMS interactions (clicks, time spent, forum activity) and demographics are used to predict success. They noted that feature engineering from raw log data is foundational and various ML models can be used. The paper also addressed ethical concerns regarding data privacy, potential algorithmic bias, and the need to develop fair models for all students. The tutorial specifically aimed to help social scientists use these ML methods.

Coelho et al. (2023) explored how the Federal University of Amazonas (UFAM) uses LA to help students succeed in introductory programming (Computer Science 1 (CS1)) courses. Their research focused on three areas: forecasting student performance, classifying exercise difficulty, and adding gamification. The team also shared their CodeBench dataset (2016-2022), which gathered detailed student interaction data (like keystrokes, revisions, and errors) from their custom-built online judge. After outlining their analytic workflow (from data collection to model analysis), the authors showed they could predict student outcomes with good accuracy (F1 scores $\approx$ 80% in early weeks, improving to $\approx$ 90% by week 6), using SHAP for interpretability. For exercise analysis, they differentiated between an exercise's inherent "complexity" and its perceived "difficulty," which they successfully predicted (F1 up to 94%) using metrics like success rates. Finally, their gamification research with CodePlay, categorized by Hexad user types (e.g., Achiever), measured engagement and found distinct interaction patterns, particularly among mobile users, suggesting possibilities for tailored game experiences.

3.5 Key Related Works

This chapter discussed many studies that are related to this dissertation, especially those that looked at how distractions and personality traits affect academic performance and how IDE logs can be used to predict future academic outcomes. This section brings together the most relevant information for this work in Table 1, which we then compare to the results of this study in Chapter 6.

Table 1 – Summary of Key Related Studies for Comparison

Study	**Key Finding**	**Relevance to This Dissertation**
(ZELL; LESICK, 2022); (MAMMADOV, 2022)	Meta-analyses showed conscientiousness as the strongest Big Five predictor of academic performance.	Provides a baseline to support or contrast with the personality findings for Class 1.

Continued on next page

Table 1 continued

Study	Key Finding	Relevance to This Dissertation
(CORAZZINI et al., 2021)	Found both conscientiousness and openness to experience positively predicted first-year university GPA.	Directly mirrors the two key traits identified in this dissertation's two separate classes.
(EMARA et al., 2025)	Identified student profiles linking personality to distraction management. High conscientiousness/openness correlated with self-regulation; high neuroticism correlated with distraction.	Directly links all three core variables: personality, distraction, and performance/regulation.
(PEREIRA; FONSECA; OLIVEIRA; CRISTEA, et al., 2021)	Used CodeBench data combined with Big Five traits to predict performance. Found Conscientiousness-related attributes (e.g., problems attempted) were predictive.	The most methodologically similar study validates the combination of the specific IDE (CodeBench) and personality assessment.
(COELHO et al., 2023); (PEREIRA; FONSECA; OLIVEIRA; OLIVEIRA, et al., 2020)	Validated that CodeBench interaction data (e.g., "problems solved successfully") is a predictor of student performance in programming.	Validates this dissertation's primary data source (CodeBench) and supports its findings on IDE metrics as predictors.

3.6 Research Gap

While existing literature covers the individual impacts of distractions, personality traits, and learning analytics on academic performance, few studies integrate all three dimensions within the context of introductory programming. Moreover, most research treats students as a homogeneous group or focuses on novices. This dissertation addresses this gap by examining the interrelationships between Big Five personality traits, self-perceived internal and external distractions, and objective programming behavior captured via IDE metrics. Comparisons between first-time learners (novices) and repeating students offer an analysis that reveals how prior experience alters the mechanisms of academic success and distraction management in computer science education.

Chapter 4

Methodology

This chapter outlines all phases of this dissertation, as illustrated in Figure 3. First, we detail the characteristics of the participants and discuss the ethical considerations. Second, we discuss data-gathering methods and the type of data. Finally, we discuss the methods we applied for data preprocessing and analysis.

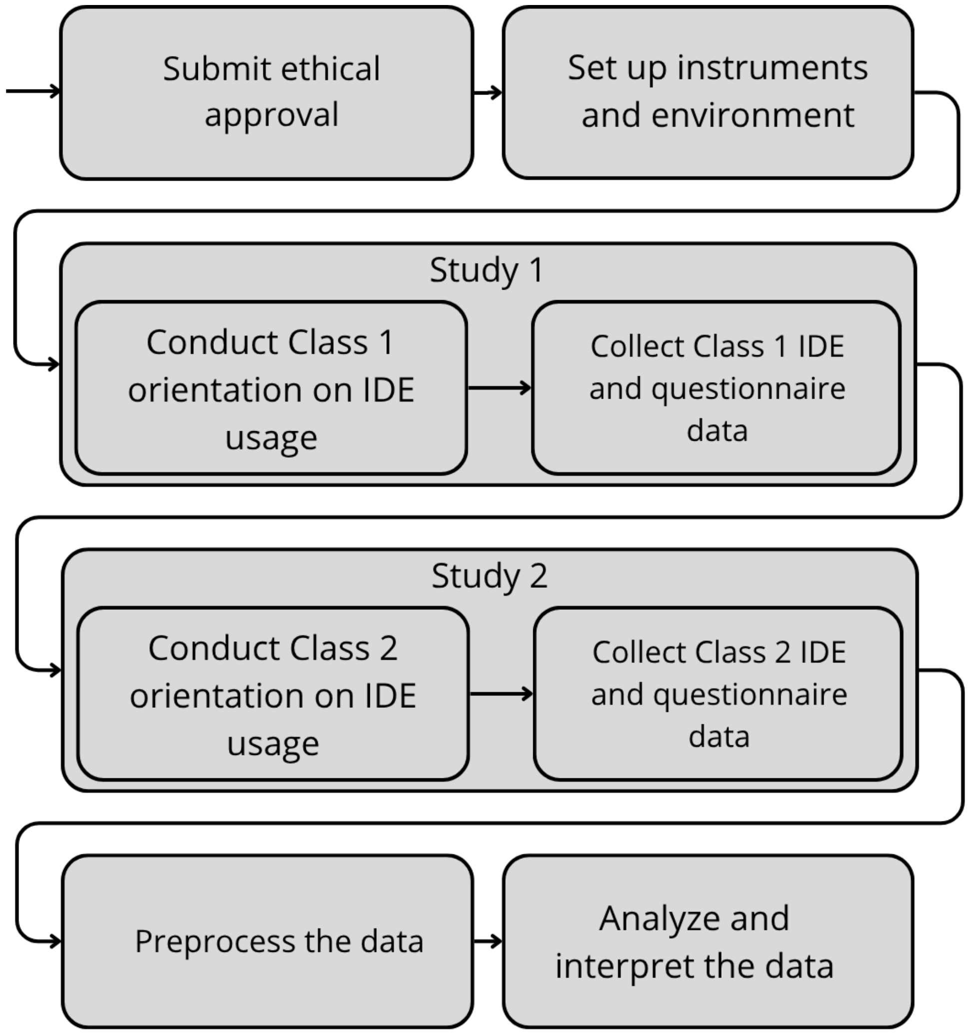

Figure 3 – Overview of the research process.

4.1 Participants and Ethical Considerations

Before running the data collection, we submitted it to the ethics committee for review and approval. After approval[1], we discussed the project with students and gathered their consent.

We collected data from two distinct cohorts of students. The first group consisted of 32 students from a pool of 64, while the second group also consisted of 32, but from a pool of 60. Both groups consisted of individuals with and without prior programming knowledge. At the time of the study, some students already had a previous degree from another field and were working in fields such as nursing, engineering, and law. The participants' ages ranged from 18 to 50, with the majority falling between 18 and 25. It is important to note that Group 1 (Class 1) consisted of first-year students, while Group 2 (Class 2) was composed primarily of repeating students—those who had previously taken an introductory programming course but either failed or withdrew.

4.2 Instruments and Data Gathering

We gathered data using two instruments: Google Forms and the CodeBench IDE. With Google Forms, we collected data related to distractions and personality (see Appendix D for their content). The questionnaire consisted of 11 questions about distractions and 20 questions about personality. We adopted a deductive approach to creating the distraction items, mapping them to constructs identified in the literature. Questions regarding external technological distractions (e.g., smartphone use, social media) were adapted from Dontre (2021) and Deng, Zhou, and Broadbent (2024). Items focusing on social and environmental distractions (e.g., noise, peer interruptions) were based on categories defined by Brady, Kim, and Cutshall (2021). Internal distractions, such as mind-wandering and anxiety, were derived from the self-regulatory and emotional categories described by Brady, Kim, and Cutshall (2021) and Deng, Zhou, and Broadbent (2024). It is important to mention that while these items were grounded in theory, the specific questionnaire used in this study did not undergo a separate psychometric validation process (e.g., Factor Analysis). For personality assessment, we used the Mini-IPIP questionnaire, a measure of the Big Five personality traits (DONNELLAN et al., 2006), adapted from the Portuguese version (OLIVEIRA, 2019). We chose to use the standard items rather than adapting them to the specific programming context (e.g., changing "I like order" to "I like to indent my code"). This decision was made to maintain the instrument's validity, as adapting items would necessitate a new validation process beyond the scope of this study. However, we anticipate that these traits will manifest in lab behaviors; for instance, Conscientiousness may translate to code organization, while Openness

[1] Certificado de Apresentação de Apreciação Ética (CAAE): 82543524.1.0000.5152

may relate to a willingness to experiment with new syntax. We utilized a 5-point Likert scale on both questionnaires, with an additional "prefer not to answer" option.

We collected very detailed data using the CodeBench IDE during lab sessions in which students solved programming exercises related to introductory concepts such as conditional structures, loops, and arrays. The platform logged detailed student interactions, including keystrokes, mouse clicks, code submissions, and changes to the browser and IDE windows, all with the corresponding timestamps. At the end of the programming sessions, the platform generated a JavaScript Object Notation (JSON) file with all the data.

We conducted a two-step data collection procedure. First, we familiarized students with the CodeBench. Each student created an account using their student ID, logged in, and then enrolled in the discipline. We conducted a first test to help students become familiar with the IDE and learn how to submit their exercises for assessment. We did it for both groups. Second, after the initial familiarization session, we conducted two additional sessions on separate days, during which we collected the data used in this work, including the questionnaire responses.

To ensure the accuracy of the findings, we only used data from lab sessions, despite allowing students to complete their exercises at home. The lab sessions consisted of two 50-minute sessions, totaling 100 minutes each.

We saved the data in Google Drive, with access restricted to the authors. The questionnaire data was converted into a Comma-Separated Values (CSV) file, while the JSON files from the CodeBench platform were initially maintained in their original JSON format. Students' data were anonymized using a unique ID, a different one from their university ID.

4.2.1 CodeBench

The Institute of Computing of the UFAM created the CodeBench, an online judge platform, with several important goals: i) to provide programming students with educational tools that make learning more fun and effective; ii) to give teachers valuable information about how their students are doing in programming courses; iii) to provide resources that make teaching easier; and iv) to encourage and support teachers in using and implementing more modern and creative ways of teaching.

Teachers can use CodeBench to give their students programming assignments, as illustrated by Figure 4. The students then have to come up with solutions and turn them in through the platform's interface. When a student turns in their work, the system immediately tells them if their answer is right or wrong. In addition, CodeBench makes it easier for students and teachers in a class to talk to each other through its messaging features. It also allows teachers to share educational materials and resources (INSTITUTE OF COMPUTING, FEDERAL UNIVERSITY OF AMAZONAS, 2025).

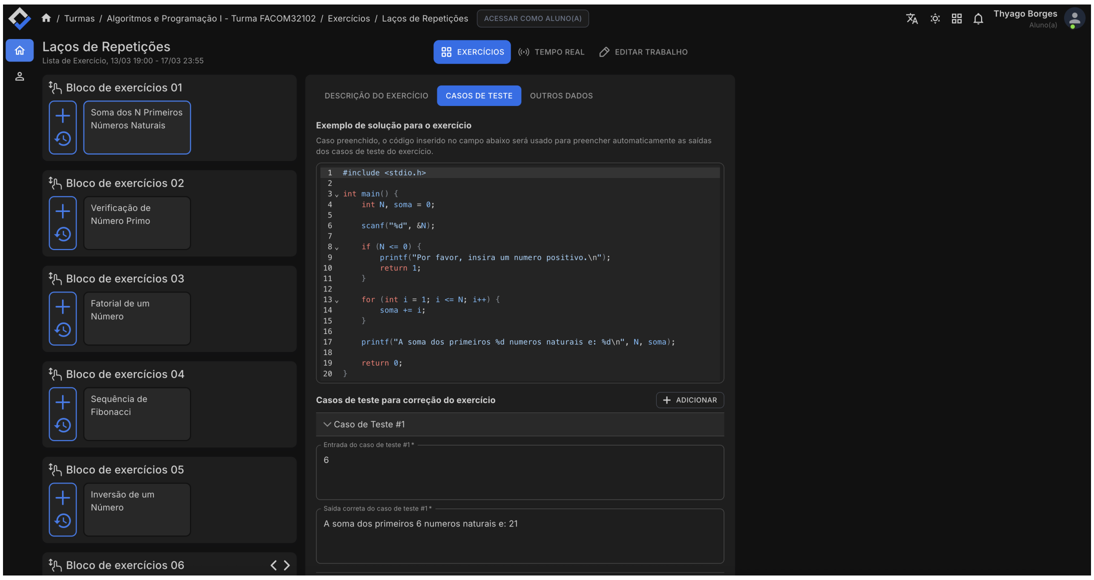

Figure 4 – CodeBench page where professors and tutors can create exercise lists.

4.3 Data Preprocessing and Analysis

To perform the preprocessing and analysis phases, we followed the steps described in Fig 5.

We used Google Colab[2] connected to Google Drive to access all the collected data. With everything connected, we converted the questionnaire and CodeBench data to a dataframe and used the Python programming language for data management. Before proceeding with data analysis, we cleaned the data by excluding participants with more than five missing questionnaire items and applying mean imputation, based on the mean value of the column, for those with fewer than five missing items.

We applied mean imputation because the proportion of missing data within retained participants was small and randomly distributed, making mean substitution a statistically defensible and minimally distortive approach. Using the column mean preserved the overall distributional properties of each variable, allowed us to retain participants who were otherwise complete, and avoided unnecessary loss of statistical power that would result from listwise deletion.

For the CodeBench data, we parsed the JSON logs and performed feature engineering to derive more interpretable variables of the programming behavior.

Following the cleaning process, we converted the distractions into two categories: internal and external. After that, we calculated the portion of internal and external distractions that each participant perceived as harmful during lab sessions. As the number of each type of distraction was imbalanced, we normalized the values using the Z-score after calculation. Finally, we assessed the personality trait values of the Mini-IPIP questionnaire according to its calculation rules.

[2] https://colab.google/

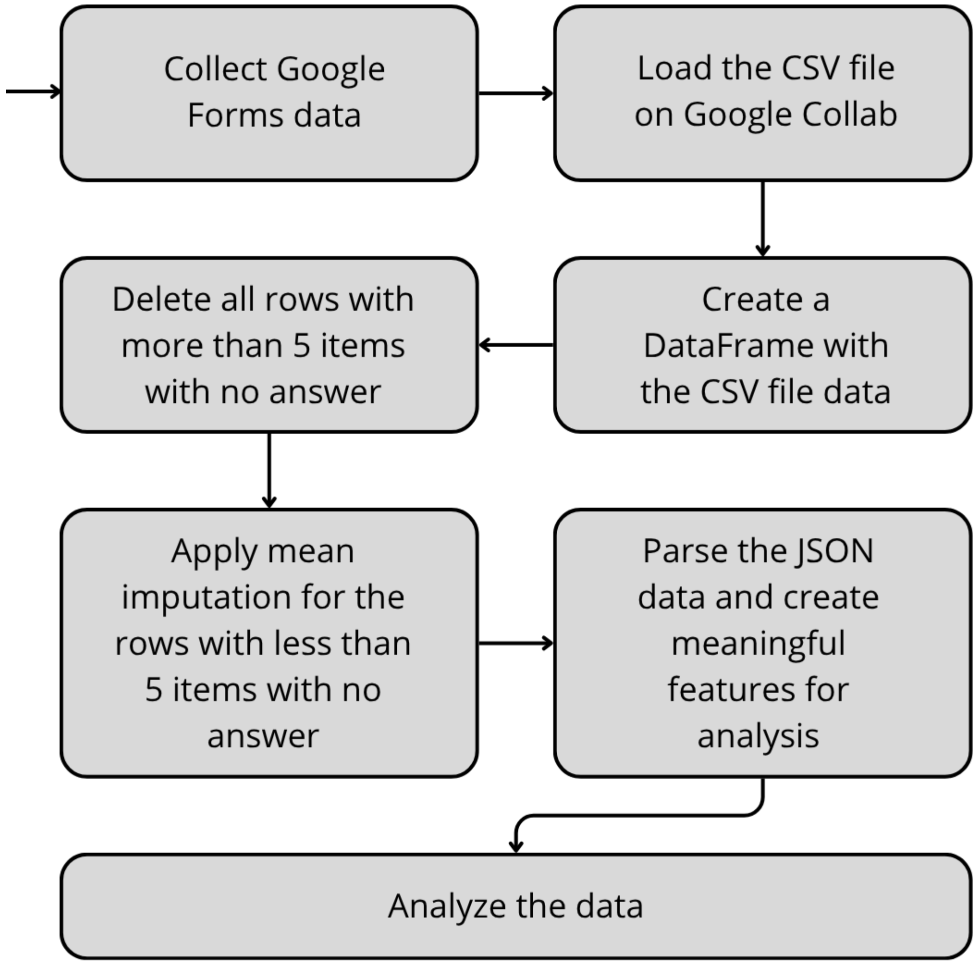

Figure 5 – Overview of data preprocessing and analysis.

With all data ready to be used, we created a new dataframe that merges distractions, personality traits, IDE variables, and students' GPAIDs, based on student ID, generated using a Universally Unique Identifier (UUID). After that, we started the statistical analysis of the data.

We calculated Spearman correlation coefficients (ρ) to assess the 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 whether perceived distraction variables or personality traits predicted IDE interaction variables.

We used Spearman's correlation because many of our variables did not follow a normal pattern or a straight-line relationship. Some measures, like distraction ratings and personality scores, were ordinal, and others were unevenly spread out. This method let us look at whether the values moved up or down together, rather than forcing a linear connection that might not fit the data. It also handled outliers better, giving us a more accurate view of how the variables in the study were related.

Finally, we used 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 tests across all moderation tests conducted.

We used OLS regression because it is a straightforward and reliable method for examining how different factors interact to influence a result. In our case, we wanted to see whether personality traits moderate (to a certain extent) the effect that internal and external distractions have on academic performance. OLS regression makes it easy to include interaction terms, allowing us to test these moderation effects directly. It also works well with our continuous outcome variables, providing results that are easy to interpret and compare. Because OLS is widely used and understood, it allowed us to analyze these relationships clearly and consistently across all our tests.

4.4 AI Statement

We used ChatGPT and Grammarly for writing assistance, editing, and grammar checking. Nevertheless, all ideas, analyses, and conclusions remain our original work, and we take full responsibility for the content's accuracy.

Chapter 5

Results

The results are organized by two main analyses: Spearman correlations to explore bivariate associations, followed by regression analyses to examine predictive relationships and moderation effects, both separated by class and only with significant results. See Appendix A to understand the variables utilized in this work. Complete tables, containing all values, are located in Appendices B and C.

5.1 Spearman Correlations

We performed Spearman correlations to assess the relationships between personality dimensions, distractions, IDE usage metrics, and academic performance. The scale used for the interpretation of correlation strengths came from (SCHOBER; BOER; SCHWARTE, 2018).

5.1.1 Personality Dimensions and Distractions

Class 1 showed a statistically significant correlation: agreeableness was positively correlated with conscientiousness ($\rho = 0.361$, $p = 0.043$). Neither internal nor external distractions demonstrated statistically significant relationships with any personality dimensions (Table 15).

Table 2 – **Class 1:** Personality Traits and Distractions

Variable Pair	ρ	p**-value**
Agreeableness - Conscientiousness	0.361	0.043*

*Significant at $p < 0.05$

Class 2 showed multiple relationships (Table 3). External distractions were negatively correlated with extraversion ($\rho = -0.453$, $p = 0.008$). Internal and external distractions were positively correlated with each other ($\rho = 0.449$, $p = 0.009$). Among personality traits, extraversion was positively correlated with agreeableness ($\rho = 0.460$, $p = 0.007$)

and negatively with neuroticism ($\rho = -0.450$, $p = 0.009$). Neuroticism was negatively correlated with agreeableness ($\rho = -0.405$, $p = 0.019$). Openness was positively correlated with conscientiousness ($\rho = 0.421$, $p = 0.015$).

Table 3 – **Class 2:** Personality Traits and Distractions

Variable Pair	ρ	p**-value**
Distractions Correlated with Predictors		
External Distractions - Extraversion	-0.453	0.008*
Internal Distractions - External Distractions	0.449	0.009*
Personality Traits Correlated with Predictors		
Extraversion - Agreeableness	0.460	0.007*
Neuroticism - Extraversion	-0.450	0.009*
Neuroticism - Agreeableness	-0.405	0.019*
Openness - Conscientiousness	0.421	0.015*

*Significant at $p < 0.05$

5.1.2 Personality, Distractions, and IDE Metrics

In Class 1, internal distractions were negatively correlated with code correctness ($\rho = -0.423$, $p = 0.016$), success rates ($\rho = -0.424$, $p = 0.016$), and successful submissions ($\rho = -0.351$, $p = 0.049$). External distractions were negatively correlated with coding activity intensity ($\rho = -0.375$, $p = 0.035$) (Table 4).

Among personality traits, conscientiousness was positively correlated with typing activity ($\rho = 0.419$, $p = 0.017$). Extraversion and agreeableness were positively correlated with submission frequency ($\rho = 0.349$, $p = 0.050$ and $\rho = 0.372$, $p = 0.036$, respectively). Neuroticism was negatively correlated with activity intensity ($\rho = -0.402$, $p = 0.022$) and positively with the pause duration ($\rho = 0.351$, $p = 0.049$).

In Class 2, internal distractions positively correlated with success rates ($\rho = 0.419$, $p = 0.015$) and code correctness ($\rho = 0.396$, $p = 0.023$). External distractions positively correlated with success rates ($\rho = 0.419$, $p = 0.015$), code correctness ($\rho = 0.400$, $p = 0.021$), and average duration per exercise ($\rho = 0.351$, $p = 0.045$) (Table 5).

Conscientiousness and openness both negatively correlated with average events per exercise ($\rho = -0.500$, $p = 0.003$ and $\rho = -0.489$, $p = 0.004$, respectively). Both traits positively correlated with pause duration (conscientiousness: $\rho = 0.351$, $p = 0.045$; openness: $\rho = 0.503$, $p = 0.003$). Extraversion negatively correlated with success rates ($\rho = -0.360$, $p = 0.040$) and code correctness ($\rho = -0.351$, $p = 0.045$).

5.1.3 Performance, Distractions, and Personality

Neither internal nor external distractions showed significant correlations with any academic performance variables (exam scores, GPA, or course completion) in either class.

Table 4 – **Class 1:** Distractions, Personality Traits, and IDE Metrics

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

*Significant at $p < 0.05$

Table 5 – **Class 2:** Distractions, Personality Traits, and IDE Metrics

Variable Pair	ρ	p**-value**
Internal Distractions and IDE Metrics		
Internal Distractions - Success Rates	0.419	0.015*
Internal Distractions - Code Correctness	0.396	0.023*
External Distractions and IDE Metrics		
External Distractions - Success Rates	0.419	0.015*
External Distractions - Code Correctness	0.400	0.021*
External Distractions - Avg Duration Per Exercise	0.351	0.045*
Personality Traits and IDE Metrics		
Conscientiousness - Avg Events Per Exercise	-0.500	0.003*
Conscientiousness - Pause Duration	0.351	0.045*
Extraversion - Success Rates	-0.360	0.040*
Extraversion - Code Correctness	-0.351	0.045*
Openness - Pause Duration	0.503	0.003*
Openness - Avg Events Per Exercise	-0.489	0.004*

*Significant at $p < 0.05$

In Class 1, conscientiousness positively correlated with exam 3 ($\rho = 0.392$, $p = 0.026$) and GPA ($\rho = 0.421$, $p = 0.016$). No other personality traits showed significant relationships with academic outcomes (Table 6).

Table 6 – **Class 1:** Predictors and Academic Performance

Variable Pair	ρ	p**-value**
Personality Traits and Academic Performance		
Conscientiousness - Exam 3	0.392	0.026*
Conscientiousness - GPA	0.421	0.016*

*Significant at $p < 0.05$

In Class 2, openness positively correlated with exam 1 ($\rho = 0.529$, $p = 0.002$). No other personality traits showed significant relationships with academic outcomes (Table 7).

Table 7 – **Class 2:** Predictors and Academic Performance

Variable Pair	ρ	p**-value**
Personality Traits and Academic Performance		
Openness - Exam 1	0.529	0.002*

*Significant at $p < 0.05$

5.1.4 Performance and IDE Metrics

In Class 1, successful submissions showed correlations with exam 3 ($\rho = 0.698$, $p < 0.001$), GPA ($\rho = 0.636$, $p < 0.001$), and exam 2 ($\rho = 0.563$, $p < 0.001$). Submission frequency was correlated with exam 3 ($\rho = 0.655$, $p < 0.001$), GPA ($\rho = 0.589$, $p < 0.001$), and exam 2 ($\rho = 0.456$, $p = 0.009$). Typing activity was correlated with exam 3 ($\rho = 0.589$, $p < 0.001$) and GPA ($\rho = 0.569$, $p < 0.001$). Additional significant correlations are shown in Table 8.

In Class 2, the total events were correlated with GPA ($\rho = 0.557$, $p < 0.001$), the final pass status ($\rho = 0.522$, $p = 0.002$), exam 3 ($\rho = 0.519$, $p = 0.002$), and exam 2 ($\rho = 0.511$, $p = 0.002$). The total duration was correlated with GPA ($\rho = 0.554$, $p < 0.001$) and other performance measures. The typing activity was correlated with GPA ($\rho = 0.598$, $p < 0.001$) and the final pass status ($\rho = 0.567$, $p < 0.001$). Additional correlations are shown in Table 9.

Table 8 – **Class 1:** Early IDE Metrics and Academic Performance

Variable Pair	ρ	p**-value**
Code Correctness		
Code Correctness - Exam 2	0.552	0.001*
Code Correctness - Exam 3	0.472	0.006*
Code Correctness - Final Pass Status	0.359	0.043*
Code Correctness - GPA	0.453	0.009*
Coding Activity Intensity		
Coding Activity Intensity - Exam 1	0.473	0.006*
Coding Activity Intensity - Exam 2	0.444	0.011*
Coding Activity Intensity - GPA	0.366	0.040*
Submission Frequency		
Submission Frequency - Exam 2	0.456	0.009*
Submission Frequency - Exam 3	0.655	< 0.001*
Submission Frequency - GPA	0.589	< 0.001*
Success Rates		
Success Rates - Exam 2	0.496	0.004*
Success Rates - Exam 3	0.475	0.006*
Success Rates - GPA	0.432	0.014*
Successful Submissions		
Successful Submissions - Exam 2	0.563	< 0.001*
Successful Submissions - Exam 3	0.698	< 0.001*
Successful Submissions - GPA	0.636	< 0.001*
Total Blur Time		
Total Blur Time - Exam 3	0.428	0.015*
Total Blur Time - GPA	0.444	0.011*
Total Deletions		
Total Deletions - Exam 3	0.424	0.016*
Total Deletions - GPA	0.454	0.009*
Total Duration		
Total Duration - Exam 3	0.356	0.045*
Total Events		
Total Events - Exam 1	0.396	0.025*
Total Events - Exam 2	0.369	0.038*
Total Events - Exam 3	0.462	0.008*
Total Events - GPA	0.464	0.008*
Total Focus Time		
Total Focus Time - Exam 3	0.431	0.014*
Total Focus Time - GPA	0.443	0.011*
Typing Activity		
Typing Activity - Exam 2	0.472	0.006*
Typing Activity - Exam 3	0.589	< 0.001*
Typing Activity - Final Pass Status	0.419	0.017*
Typing Activity - GPA	0.569	< 0.001*

*Significant at $p < 0.05$

Table 9 – **Class 2:** Early IDE Metrics and Academic Performance

Variable Pair	ρ	p**-value**
Total Duration		
Total Duration - GPA	0.554	< 0.001*
Total Duration - Final Pass Status	0.502	0.003*
Total Duration - Exam 2	0.496	0.003*
Total Duration - Exam 3	0.470	0.006*
Total Events		
Total Events - GPA	0.557	< 0.001*
Total Events - Final Pass Status	0.522	0.002*
Total Events - Exam 3	0.519	0.002*
Total Events - Exam 2	0.511	0.002*
Submission Frequency		
Submission Frequency - Exam 3	0.498	0.003*
Submission Frequency - Final Pass Status	0.422	0.014*
Submission Frequency - GPA	0.412	0.017*
Successful Submissions		
Successful Submissions - GPA	0.592	< 0.001*
Successful Submissions - Final Pass Status	0.544	0.001*
Successful Submissions - Exam 3	0.531	0.001*
Successful Submissions - Exam 2	0.448	0.009*
Total Focus Time		
Total Focus Time - Exam 3	0.368	0.035*
Total Focus Time - GPA	0.351	0.045*
Total Blur Time		
Total Blur Time - Exam 3	0.353	0.044*
Total Blur Time - GPA	0.344	0.050*
Typing Activity		
Typing Activity - GPA	0.598	< 0.001*
Typing Activity - Final Pass Status	0.567	< 0.001*
Typing Activity - Exam 3	0.538	0.001*
Typing Activity - Exam 2	0.425	0.014*
Total Deletions		
Total Deletions - GPA	0.483	0.004*
Total Deletions - Exam 3	0.474	0.005*
Total Deletions - Final Pass Status	0.473	0.005*
Total Deletions - Exam 2	0.450	0.009*

*Significant at $p < 0.05$

5.2 Multiple Regression Analysis

5.2.1 Class-Specific Determinants of Programming Performance

In Class 1, internal distractions negatively predicted submission success rates ($\beta = -0.461$, $p = 0.017$, $R^2 = 0.354$) and overall correctness ($\beta = -0.688$, $p = 0.023$, $R^2 = 0.303$). Extraversion positively predicted 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 positively predicted typing behaviors ($\beta = 682.74$, $p = 0.050$, $R^2 = 0.454$). External distractions showed no significant independent effects (Table 10).

Table 10 – **Class 1:** 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 $p < 0.05$

In Class 2, neither internal nor external distractions showed significant independent effects. Openness positively predicted exam 1 performance ($\beta = 3.304$, $p = 0.023$, $R^2 = 0.321$) and pause duration ($\beta = 0.516$, $p = 0.032$, $R^2 = 0.315$). Agreeableness positively predicted success rates ($\beta = 0.134$, $p = 0.015$, $R^2 = 0.406$) and overall correctness ($\beta = 0.096$, $p = 0.039$, $R^2 = 0.332$), and negatively predicted the pause duration ($\beta = -0.515$, $p = 0.040$). Conscientiousness negatively predicted the total runs ($\beta = -30.839$, $p = 0.008$, $R^2 = 0.266$) (Table 11).

Table 11 – **Class 2:** Internal Distractions and Personality Traits as Predictors

Predictor - Outcome	β	p**-value**	R^2
Distractions as Predictors			
No significant individual predictors from Distraction models.			
Personality Traits as Predictors			
Conscientiousness - Total Runs	-30.839	0.008*	0.266
Agreeableness - Success Rates	0.134	0.015*	0.406
Openness - Exam 1	3.304	0.023*	0.321
Openness - Pause Duration	0.516	0.032*	0.315
Agreeableness - Pause Duration	-0.515	0.040*	
Agreeableness - Overall Correctness	0.096	0.039*	0.332

*Significant at $p < 0.05$

5.2.2 Personality Traits as Moderators

We conducted 190 interaction tests across all combinations of personality traits, distraction types, and outcome variables in each class. The FDR correction was applied to control for multiple comparisons.

In Class 1, 14 interactions showed statistical significance at $p < 0.05$ before correction (7.4% of tests). After applying the FDR correction with $q = 0.05$, zero interactions remained statistically significant. Bonferroni correction also yielded zero significant interactions (Table 12).

Table 12 – **Class 1:** 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

In Class 2, 3 interactions showed statistical significance at $p < 0.05$ before correction (1.6% of tests), below the 9.5 interactions expected by chance. After applying the FDR correction with $q < 0.05$, zero interactions remained statistically significant. Bonferroni correction also yielded zero significant results (Table 13).

Table 13 – **Class 2:** Multiple Testing Correction Results for Moderation Analysis

Testing Outcome	**Count**
Total moderation tests conducted	190
Uncorrected significant interactions ($p < 0.05$)	3 (1.6%)
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)	0.015

Note: FDR = False Discovery Rate

5.3 Summary of Findings Related to Research Questions

This section summarizes the results of the statistical analyses in direct relation to the research questions (RQs) established in Chapter 1.

- ❑ **RQ1: How do personality traits and self-reported distractions relate to programming behavior?** The results showed that personality traits relate to how students engage with the IDE. In novices (Class 1), Conscientiousness correlated with higher typing activity, while in repeaters (Class 2), Conscientiousness and Openness were linked to longer pause durations and fewer events per exercise. Distractions also played a role: internal distractions were negatively associated with correctness and success rates for novices, while repeaters showed a positive correlation, suggesting different management strategies.

- **RQ2: How do personality traits and distractions predict academic performance?** Conscientiousness was the predictor for novices (Class 1), correlating positively with GPA and exam scores. For repeaters (Class 2), Openness emerged as a predictor of early exam performance. Distractions did not show a direct linear correlation with final academic outcomes in either class, despite their association with lab-session behaviors.

- **RQ3: Can early IDE metrics predict subsequent academic performance?** There was evidence across both classes that early IDE behaviors are predictive of performance. Successful submissions and typing activity were consistent predictors of GPA and exam grades, particularly for novices, confirming that process-oriented data captured via CodeBench can serve as early warning signs or performance indicators.

- **RQ4: Do personality traits moderate the relationship between distractions and programming outcomes?** While several potential interactions were initially identified, none remained statistically significant after FDR and Bonferroni corrections. The results suggest that, within this sample size, the direct effects of personality and distractions are more observable than their interactive (moderating) effects.

- **RQ5: How does prior learning experience influence these relationships?** Prior experience (novice vs. repeater) altered the dynamics between the variables. Novices relied more on Conscientiousness for success and were more hindered by internal distractions. Repeaters' performance was more closely linked to Openness, and they exhibited different behavioral patterns in the IDE, such as longer pauses and a relationship with self-reported distractions.

Chapter 6

Discussion

6.1 Interpretation of Correlation Findings

This section discusses the results. It is important to consider the context of the classes, with class 1 representing novice students and class 2 repeating students.

6.1.1 Personality and Distraction Relationships

The findings indicate differences between the two classes in relationships between personality dimensions and distraction susceptibilities. Class 1 results suggest that personality and distractions functioned independently from one another. A medium-strength correlation existed between agreeableness and conscientiousness. However, it is important to consider a potential bias in self-reporting: highly conscientious students may report more distractions due to higher self-expectations and a lower tolerance for lapses in focus, rather than an objective increase in distraction frequency. Class 2 results suggest that extraversion may offer some protection against external distractions. Extraverted students reported fewer external distractions. The two types of distractions may co-occur within the individual. Students susceptible to one type of distraction were also likely susceptible to the other type.

Class 2 personality trait correlations indicated many patterns consistent with established personality theory. The negative relationship between extraversion and neuroticism aligned with documented personality structure, along with their opposing relationships with agreeableness. The positive correlation between openness and conscientiousness suggests these traits may work together in academic settings.

6.1.2 Distractions and Programming Behavior

The analysis of IDE metrics revealed different patterns between the two classes. How distractions and personality traits correlate with programming behavior differed across classes. Distractions in Class 1 had a majority of negative relationships with performance metrics. Class 2 had positive relationships with performance metrics that suggest different underlying mechanisms.

In Class 1, internal distractions were associated with reduced programming performance. This demonstrates how internal distractions disrupted cognitive efforts needed in developing correct code. External distractions showed a relationship with decreased coding activity intensity rather than influencing performance metrics directly. This suggests that external distractions resulted in disrupted engagement. They did not negatively influence code quality when students were working on code.

Class 2 presented a different pattern. Both internal and external distractions showed positive correlations with performance metrics. These results reflect a relationship in which higher-performing students in this class were conscious of or inclined to report their distractions. Alternatively, what is captured as "external distraction" (e.g., tab switching or talking) might represent learning strategies. For instance, switching tabs often indicates consulting documentation or searching for solutions, which are programming skills. Similarly, social interactions in the lab may reflect collaborative strategies like pair programming or peer support, which can enhance understanding.

These divergent findings between classes imply that contextual elements may moderate the relationship between distractions, personality, and programming behavior. Such elements include course format, teaching method, student composition, or measurement timing. The positive distraction performance correlations in Class 2 demand caution in interpretation. They underscore the importance of considering class contexts when drawing conclusions about these relationships.

6.1.3 Personality Traits and Programming Behavior

In Class 1, personality traits were associated with distinct coding patterns. Conscientiousness promoted active typing engagement. Extraversion and agreeableness were associated with frequent submission behavior, suggesting that these traits may promote active engagement with the programming environment. Neuroticism was shown to have a relationship with indicators of less smooth coding flow. This included decreased activity intensity and longer pauses between actions, reflecting greater hesitation or anxiety during programming tasks.

The personality IDE metric relationships in Class 2 exhibited different patterns from those encountered in Class 1. Conscientiousness and openness both exhibited negative correlations with the average number of events per exercise. This indicates that students higher in these traits may have adopted more efficient problem-solving strategies with fewer trial-and-error attempts. Both traits were also positively correlated with pause duration, suggesting deliberate and reflective programming strategies. Extraversion showed negative correlations with success rates and code correctness in Class 2. This deviates from its positive association with submission frequency in Class 1.

6.1.4 Personality, Distractions, and Academic Performance

The analysis of academic performance indicated different personality-achievement relationships between classes. Different traits were significant indicators in different situations. Distractions showed minimal associations with academic outcomes in both classes.

In Class 1, conscientiousness was the strongest correlate of academic success. This relationship suggests that conscientious, organized, disciplined, and goal-directed behaviors associated with conscientiousness proved effective in sustaining academic success in Class 1. This relationship was stronger for course performance later in the course, such as exam 3 and GPA, than early performance. This indicates that conscientious studying and persistence were becoming important as course material built up and was developed. The other personality traits did not have significant relationships with academic outcomes in Class 1. Conscientiousness-related behaviors were likely the personality mechanisms leading to academic success in Class 1.

A different pattern was present in Class 2. Openness to experience was the significant personality correlate of academic performance. This indicates that intellectual curiosity, creativity, and comfort with abstract thought provided the most benefit for early course performance in Class 2. The specificity of this relationship to exam 1, rather than later exams or overall GPA, suggests that openness provided some advantage in the early phases of learning.

Conscientiousness did not have significant effects in Class 2. Openness did not have effects in Class 1. This demonstrates variability in which personality traits predict academic success between educational contexts.

Neither internal nor external distractions exhibited significant relationships with any academic performance variables. This consistent finding across two independent samples suggests that academic performance may be more buffered against momentary distractions than real-time programming tasks. Though distractions revealed relationships with immediate IDE-based performance measures, this occurred primarily in Class 1. This did not manifest in any measurable effects on final academic performance. This trend demonstrates that personality-related behaviors showed stronger associations with academic success than managing momentary attention lapses. Conscientiousness in Class 1 and openness in Class 2 were the dominant factors.

6.1.5 Early IDE Metrics as Predictors of Academic Success

Early IDE metrics analysis revealed correlational relationships with subsequent academic performance in both classes. Programming behavior patterns measured early in the course were predictors of later achievement. Both classes showed associations between IDE metrics and academic outcomes. They differed in which metrics emerged as the best predictors and in the relative strength of these relationships across different performance measures.

In Class 1, successful submissions proved to be a reliable predictor across all academic measures. This pattern suggests that early programming success, as measured by the total number of correctly completed exercises, is associated with later academic accomplishment across multiple assessment types. Submission frequency also showed predictive capability. This means that students who attempted problems, regardless of immediate success, developed stronger programming skills over time. Coding activity intensity, measured through typing events, showed consistent correlations with later performance. This indicates that engaged programming behavior was associated with better learning outcomes.

Performance quality metrics also proved predictive in our study. This indicates that both the quantity and quality of early programming practice contributed independently to subsequent academic success. Engagement indicators further supported these patterns. Total events correlated greatly across all exams and GPA. Overall time spent in the IDE environment, whether focused or sometimes distracted, was associated with better outcomes. Exam 3 emerged as the outcome most associated with early IDE behavior, while exam 1 exhibited weaker correlations. This means that programming metrics may become more predictive as course complexity increases and foundational concepts are introduced.

Class 2 demonstrated a distinct predictive pattern. Volume-based metrics emerged as the strongest correlates of academic performance. Total events and total duration showed the highest correlations. This suggests that the amount of interaction with the programming environment was predictive in this class. Typing activity demonstrated predictive power. Active coding engagement, as measured by keystroke activity, was associated with academic success across all major outcomes. Successful submissions also showed correlations. This indicates that achievement of correct solutions remained an important predictor despite the stronger emphasis on volume metrics in this class.

Total deletions consistently emerged as a predictor across numerous outcomes. This finding suggests that high deletion counts likely represent code improvement and active refinement rather than simple trial and error. In the context of "effective" learners, as described in previous literature, frequent deletions often indicate a willingness to refactor and optimize code, signaling engagement with the problem-solving process. Both total focus time and total blur time exhibited associations compared to other metrics. This indicates that attention patterns were less predictive than overall engagement volume in this class.

When comparing the two classes, differences emerge in the relative predictive power of different IDE metrics. Class 1 showed stronger differentiation between success-based metrics and volume metrics. Success metrics demonstrated associations with later exams. In contrast, Class 2 showed uniform predictive strength across both volume and success metrics. Volume-based measures emerged as slightly stronger predictors.

Both classes revealed that exam 3 and GPA were, in general, more associated with early IDE metrics than exam 1. This supports the understanding that earlier programming practice has cumulative effects that become evident as the course material builds upon foundational ideas. The consistency of these findings across two independent classes furnishes evidence that early IDE behavior patterns capture meaningful individual differences in programming skill development. These differences translate into subsequent academic achievement, despite differences in metric rankings.

6.2 Interpretation of Regression Findings

6.2.1 Independent Effects of Distractions and Personality

The multiple regression analysis revealed different patterns between the two classes. Class 1 showed internal distractions as the dominant predictor. Class 2 demonstrated personality traits as the primary independent influences.

In Class 1, internal distractions emerged as the most robust predictor. They maintained significant effect sizes when controlling for personality and external factors. These negative coefficients indicate that each unit increase in internal distraction was associated with decrements in both the rate of successful submissions and the overall correctness of code produced. This occurred after accounting for individual differences in personality. This confirms the independent influence of internal distractions on programming performance quality.

Among personality traits in Class 1, extraversion facilitated active programming practice. This translated into both greater coding activity and completed exercises. Conscientiousness enhanced typing behaviors. This indicates that conscientious students engaged in extensive coding activity independent of other factors. External distractions showed no significant independent effects in the multiple regression framework for Class 1. This suggests that their bivariate associations with coding activity intensity did not represent unique variance once other predictors were controlled. The explained variance in several models indicates that these predictors captured meaningful portions of individual differences in programming behavior. The modest sample size necessitates cautious interpretation of effect sizes.

Class 2 presented a different regression pattern. Personality traits emerged as the predictors, and distractions showed no independent effects. Neither internal nor external distractions demonstrated significant unique variance in predicting any IDE metrics or academic outcomes when controlling for personality traits and other factors. This contrasts with the strong distraction effects observed in Class 1.

In Class 2, openness predicted exam 1 performance. This confirms its role in early academic achievement independent of other personality dimensions and distractions. Openness also predicted longer pause duration. This suggests that students higher in openness adopted reflective programming approaches after controlling for other traits.

Agreeableness emerged as a multifaceted predictor. It showed significant positive effects on success rates and overall correctness, while negatively predicting pause duration. This pattern suggests that agreeable students achieved better programming outcomes through efficient, less hesitant coding behavior. Conscientiousness predicted fewer total runs. This indicates deliberate testing strategies that required fewer execution attempts to achieve correct solutions. The explained variance in Class 2 models demonstrates that personality traits accounted for portions of variance in both IDE metrics and academic performance in this class.

6.2.2 Contrasting Patterns Between Classes

The contrasting regression findings between classes reveal differences in the independent influence of distractions versus personality traits on programming outcomes. In Class 1, internal distractions maintained predictive power when controlling for personality. This suggests that attentional control represented a distinct pathway to programming performance separate from trait-level individual differences. In Class 2, personality traits dominated the regression models, while distractions contributed no unique variance. This indicates that stable individual differences rather than momentary attentional lapses were the primary determinants of programming behavior and achievement in this context.

These divergent patterns may reflect differences in course structure, task demands, or student populations that changed which individual difference dimensions most impacted programming outcomes. The lack of distraction effects in Class 2's regression models is noteworthy given the positive bivariate correlations seen between distractions and performance in that class. This suggests that these associations were driven by third variables, likely personality traits, rather than representing direct causal relationships. The consistent importance of personality traits across both classes underscores the value of considering stable individual differences when understanding programming learning processes. Different traits emerged in each class.

6.3 Moderation Analysis Interpretation

6.3.1 Absence of Moderation Effects

The comprehensive moderation analyses across both classes converge on a consistent conclusion. Personality traits do not significantly moderate the relationship between distractions and programming outcomes in these samples. Despite testing 190 possible interactions in each class, no moderation effects survived appropriate statistical correction for multiple comparisons. These tests encompassed all theoretically plausible combinations of Big Five traits, internal and external distractions, and various IDE and performance metrics.

This pattern of null findings has theoretical implications. It means that the effects of distractions on programming behavior are similar across different personality profiles. They are not influenced or altered by individual differences in traits such as conscientiousness, neuroticism, or openness to experience. The absence of moderation effects across two independent classes heightens confidence in this conclusion. It demonstrates consistency despite dissimilarities in the base relationships between predictors and outcomes observed in each class.

6.3.2 Methodological Considerations

The elevation above the expected baseline in Class 1 initially indicated potential moderation patterns. Uncorrected results suggested patterns such as conscientiousness moderating internal distractions and openness showing susceptibility to external distractions. Nevertheless, these patterns did not survive appropriate statistical correction. They should be considered exploratory observations needing replication in bigger samples rather than confirmed findings. The evidence of overfitting, reflected in a negative average adjusted R^2, further highlighted the limitations of complex interaction modeling with the available sample size. This denotes that the models were fitting noise rather than accurately capturing the true population relationships.

In Class 2, the lower rate of uncorrected findings compared to Class 1 points to the fact that Class 2 data furnished less evidence for moderation effects. The observed significant interactions likely meant chance variation rather than true moderating relationships. The average adjusted R^2 in Class 2, while slightly positive unlike Class 1, remained near zero. It indicated minimal explanatory power for the interaction models before considering multiple testing issues.

These results should be interpreted within the context of the sample sizes and the large number of tests performed. While the statistical corrections properly controlled for false positive inflation, the limited sample sizes may have diminished power to detect genuine but small moderation effects. Future research with larger samples may be needed to rule out small to moderate moderation effects that the current study was unable to detect.

6.4 Pedagogical Implications

The findings of this study suggest several avenues for educational intervention tailored to student profiles.

- ❏ **Personality-Informed Interventions:** For students with lower Conscientiousness, instructors could implement more structured goal-setting frameworks and regular progress check-ins to compensate for lower self-discipline. For those high in Neuroticism, who may be prone to anxiety-induced hesitation (as seen in longer pause durations), creating a low-stakes practice environment with immediate, constructive feedback could help build confidence.
- ❏ **Distraction Management:** Recognizing that "distractions" like tab switching can be learning strategies, instructors should focus on teaching effective information retrieval and time management rather than simply blocking external stimuli.
- ❏ **Targeted Feedback:** Using early IDE metrics (e.g., typing activity, submission frequency), instructors can identify at-risk students (e.g., "blind-trial" learners or disengaged students) in the first few weeks and intervene with personalized feedback before they fall behind.

Chapter 7

Final Considerations

This study examined how personality traits and self-reported distractions relate to programming performance and academic outcomes in two groups of undergraduate information systems students. The groups consisted of first-time learners (Class 1) and repeating learners (Class 2). Comprehensive IDE interaction data were combined with the course achievement measures.

7.1 Core Findings

The results showed that the level of experience shaped the relationships among personality, distractions, and performance. In Class 1, internal distractions were associated with lower programming performance. In Class 2, distraction effects were not present after controlling for personality. The personality–distraction correlations also differed between classes. This suggests that previous course experience may influence attention control and self-regulation mechanisms.

Personality traits predicted academic success in class-specific ways. For first-time students, conscientiousness was the main predictor of exam and GPA outcomes. This highlights the importance of effortful control and persistence in early learning. Among repeating students, openness to experience predicted early exam performance. This indicates that intellectual flexibility and curiosity supported re-engagement with familiar material. This shift from conscientiousness to openness suggests that different motivational and cognitive characteristics contribute to success at different learning stages.

Early IDE metrics predicted later academic performance in both classes. Measures reflecting engagement and early success were related to subsequent exam scores and GPA. Such measures included successful submissions, typing activity, and total events. This indicates that early programming behavior captures meaningful individual differences in learning progress. These findings support the use of learning analytics systems such as CodeBench to identify at-risk students early in the semester.

No moderation effects were found between personality traits and distractions after correcting for multiple comparisons. This suggests that the influence of distractions on programming performance operates similarly across personality profiles. This conclusion is drawn within the constraints of the current sample size.

7.2 Implications

The results emphasize the importance of considering the level of experience when designing interventions. Novice programmers may benefit from approaches that encourage task persistence and reduce internal distraction. Structured goal-setting and focus management training are examples of such approaches. Repeating students, in contrast, may benefit from strategies that promote openness and cognitive flexibility. These strategies should encourage the exploration of alternative problem-solving methods. They should also build resilience after previous course attempts.

7.3 Contributions

In addition to the empirical results found in this study, we also contribute to the methodological tools for research in computer science education. In particular, our work developing an initial version of a laboratory-specific distraction questionnaire is a first step toward providing a new tool that can be used by researchers studying CS education. The questionnaire was developed through a synthesis of existing conceptualizations of digital, social, and internal distractions from prior literature to provide a structured means to measure the nature of student interruptions occurring while they are in a programming lab. As such, at this point, the questionnaire is primarily a research tool; however, its development provides a foundation for the development of future tools to assess the "distractions" present in technical learning environments.

7.4 Limitations and Future Directions

While there are many strengths of this study, it has limitations. We used small sample sizes, and the distractions experienced by participants were reported based upon self-report data. An additional problem regarding the instrumentation was that the distraction questionnaire, although based on previous literature, was never subjected to a systematic psychometric evaluation, i.e., neither a Factor Analysis nor an alpha-Cronbach coefficient was computed to assess the reliability of the instrument. Therefore, the results from the subtypes of distractions should be considered with caution given the lack of validation. Furthermore, the use of a single institution limits the ability to generalize these findings.

In future studies it will be important to systematically evaluate the validity and reliability of the distraction questionnaire so as to possibly revise items for better clarity and to provide evidence for the factor structure of the instrument. Studies should also utilize objective measures of distraction (i.e., eye-tracking and keystroke-based inference of focus) to supplement the self-reporting used here. Multiple institutions and longitudinal designs over multiple semesters would further increase the robustness of the results. Manipulating distraction in experimental designs and exploring qualitatively how students perceive distraction management can help understand the mechanisms of the observed relationships between distractions and performance.

7.5 Publications

This study resulted in two conference papers and one workshop paper:

- ❏ Investigação da Relação entre Traços de Personalidade e Distrações no Curso de Introdução à Programação. Anais do **V Simpósio Brasileiro de Educação em Computação (EDUCOMP)**. Juiz de Fora/MG: SBC, 2025. (BORGES E SILVA; ARAÚJO; PEREIRA JÚNIOR, 2025a).
  This paper presents the analyses we conducted to investigate whether there were correlations between self-perceived distractions and personality traits using data collected from two cohorts of information systems students who completed the course in 2024. The data was not used in this dissertation, but we used the feedback to organize the questionnaires for the 2025 cohort of students.

- ❏ Investigação de distrações em cursos de introdução à programação com técnicas de Learning Analytics. In: ANAIS Estendidos do V Simpósio Brasileiro de Educação em Computação (EDUCOMP) - **Workshop de Teses e Dissertações em Educação em Computação**. Juiz de Fora/MG: SBC, 2025. (BORGES E SILVA; ARAÚJO; PEREIRA JÚNIOR, 2025b).
  This workshop paper presents this dissertation project proposal discussed with Brazilian experts in the field of computer science education.

- ❏ An Empirical Investigation of Personality Traits, Self-Perceived Distractions, and Programming Performance in an Introductory Programming Class. In: ANAIS do **XXXVI Simpósio Brasileiro de Educação em Computação (SBIE)**. Curitiba/PR: SBC, 2025. (BORGES E SILVA et al., 2025).
  This paper presents the findings of this dissertation regarding Class 1, as we were still collecting data from Class 2 at the time of writing.

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Appendix

APPENDIX A

Variable Definitions and Descriptions

Table 14 – Variable Definitions and Descriptions

Variable Name	**Description**
Personality Traits (Big Five)	
Agreeableness	Tendency to be cooperative, trusting, and considerate.
Conscientiousness	Degree of organization, self-discipline, and goal-directed behavior.
Extraversion	Level of sociability, assertiveness, and seeking external stimulation.
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	
Activity & Intensity (Typing, Events, Activity Rates, Intensity)	Measures of code entry frequency, keyboard interaction, and general level of active engagement with the IDE environment.

Continued on next page

Table 14 continued

Variable Name	Description
Submission Efficacy (Successful Submissions, Success Rates, Correctness)	Metrics for the quality and success of output: number of correct submissions, percentage of successful submissions, and accuracy of code solutions.
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, 2, 3	Performance score on the respective course examinations.
GPA	Overall Grade Point Average in the course.
Succeeding in the class	Binary outcome indicating whether the student passed the course.

APPENDIX B

Class 1 Complete Tables

Table 15 – Spearman Correlations: Personality Traits 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
Extraversion - Agreeableness	0.345	0.053
Openness - Conscientiousness	0.236	0.193
Internal Distractions - External Distractions	0.257	0.156
Extraversion - Conscientiousness	0.221	0.225
Openness - Agreeableness	0.223	0.220

*Significant at $p < 0.05$

Table 16 – Spearman Correlations: Distractions, Personality Traits, and IDE Metrics

Variable Pair	ρ	p-value
Internal Distractions and IDE Metrics		
Internal Distractions - Avg Duration Per Exercise (min)	0.209	0.251
Internal Distractions - Avg Events Per Exercise	0.001	0.998
Internal Distractions - Avg Time Between Events (sec)	0.300	0.096
Internal Distractions - Code Correctness	-0.423	0.016*
Internal Distractions - Coding Activity Intensity	-0.279	0.122
Internal Distractions - Submission Frequency	-0.015	0.935
Internal Distractions - Success Rates	-0.424	0.016*
Internal Distractions - Successful Submissions	-0.351	0.049*
Internal Distractions - Total Blur Time	-0.112	0.541
Internal Distractions - Total Deletions	-0.091	0.622
Internal Distractions - Total Duration (min)	0.065	0.724

Continued on next page

Table 16 continued

Variable Pair	ρ	p**-value**
Internal Distractions - Total Events	-0.218	0.231
Internal Distractions - Total Focus Time	-0.132	0.470
Internal Distractions - Total Runs	0.033	0.860
Internal Distractions - Typing Activity	-0.269	0.137
External Distractions and IDE Metrics		
External Distractions - Avg Duration Per Exercise (min)	0.004	0.981
External Distractions - Avg Events Per Exercise	-0.202	0.269
External Distractions - Avg Time Between Events (sec)	0.141	0.441
External Distractions - Code Correctness	0.081	0.659
External Distractions - Coding Activity Intensity	-0.375	0.035*
External Distractions - Submission Frequency	-0.048	0.794
External Distractions - Success Rates	0.059	0.748
External Distractions - Successful Submissions	0.098	0.592
External Distractions - Total Blur Time	-0.224	0.219
External Distractions - Total Deletions	-0.328	0.067
External Distractions - Total Duration (min)	0.037	0.840
External Distractions - Total Events	-0.161	0.379
External Distractions - Total Focus Time	-0.210	0.250
External Distractions - Total Runs	-0.149	0.417
External Distractions - Typing Activity	-0.222	0.222
Personality Traits and IDE Metrics		
Agreeableness - Avg Duration Per Exercise (min)	0.243	0.180
Agreeableness - Avg Events Per Exercise	0.061	0.739
Agreeableness - Avg Time Between Events (sec)	-0.054	0.770
Agreeableness - Code Correctness	-0.187	0.305
Agreeableness - Coding Activity Intensity	0.043	0.815
Agreeableness - Submission Frequency	0.372	0.036*
Agreeableness - Success Rates	-0.296	0.100
Agreeableness - Successful Submissions	0.011	0.952
Agreeableness - Total Blur Time	0.042	0.821
Agreeableness - Total Deletions	0.160	0.383
Agreeableness - Total Duration (min)	0.308	0.086
Agreeableness - Total Events	0.099	0.589
Agreeableness - Total Focus Time	0.034	0.854
Agreeableness - Total Runs	0.103	0.573
Agreeableness - Typing Activity	0.178	0.331

Continued on next page

Table 16 continued

Variable Pair	ρ	p**-value**
Conscientiousness - Avg Duration Per Exercise (min)	-0.068	0.710
Conscientiousness - Avg Events Per Exercise	-0.087	0.636
Conscientiousness - Avg Time Between Events (sec)	-0.076	0.681
Conscientiousness - Code Correctness	0.204	0.262
Conscientiousness - Coding Activity Intensity	0.093	0.611
Conscientiousness - Submission Frequency	0.203	0.264
Conscientiousness - Success Rates	0.157	0.390
Conscientiousness - Successful Submissions	0.286	0.112
Conscientiousness - Total Blur Time	0.155	0.396
Conscientiousness - Total Deletions	0.166	0.363
Conscientiousness - Total Duration (min)	0.205	0.259
Conscientiousness - Total Events	0.272	0.132
Conscientiousness - Total Focus Time	0.145	0.429
Conscientiousness - Total Runs	0.003	0.986
Conscientiousness - Typing Activity	0.419	0.017*
Extraversion - Avg Duration Per Exercise (min)	0.025	0.893
Extraversion - Avg Events Per Exercise	0.094	0.609
Extraversion - Avg Time Between Events (sec)	0.067	0.715
Extraversion - Code Correctness	-0.003	0.985
Extraversion - Coding Activity Intensity	0.029	0.876
Extraversion - Submission Frequency	0.349	0.050*
Extraversion - Success Rates	-0.123	0.502
Extraversion - Successful Submissions	0.191	0.295
Extraversion - Total Blur Time	0.237	0.192
Extraversion - Total Deletions	0.128	0.486
Extraversion - Total Duration (min)	0.166	0.364
Extraversion - Total Events	0.197	0.279
Extraversion - Total Focus Time	0.231	0.204
Extraversion - Total Runs	0.102	0.577
Extraversion - Typing Activity	0.256	0.157
Neuroticism - Avg Duration Per Exercise (min)	0.034	0.852
Neuroticism - Avg Events Per Exercise	-0.076	0.680
Neuroticism - Avg Time Between Events (sec)	0.351	0.049*
Neuroticism - Code Correctness	0.120	0.514
Neuroticism - Coding Activity Intensity	-0.402	0.022*
Neuroticism - Submission Frequency	-0.141	0.442

Continued on next page

Table 16 continued

Variable Pair	ρ	p**-value**
Neuroticism - Success Rates	0.142	0.437
Neuroticism - Successful Submissions	0.110	0.548
Neuroticism - Total Blur Time	-0.230	0.205
Neuroticism - Total Deletions	-0.114	0.533
Neuroticism - Total Duration (min)	-0.005	0.978
Neuroticism - Total Events	-0.267	0.139
Neuroticism - Total Focus Time	-0.233	0.199
Neuroticism - Total Runs	-0.097	0.598
Neuroticism - Typing Activity	-0.187	0.305
Openness - Avg Duration Per Exercise (min)	-0.093	0.611
Openness - Avg Events Per Exercise	-0.115	0.529
Openness - Avg Time Between Events (sec)	-0.072	0.694
Openness - Code Correctness	0.085	0.646
Openness - Coding Activity Intensity	0.182	0.320
Openness - Submission Frequency	0.105	0.566
Openness - Success Rates	0.006	0.975
Openness - Successful Submissions	0.048	0.792
Openness - Total Blur Time	0.001	0.997
Openness - Total Deletions	0.109	0.554
Openness - Total Duration (min)	0.006	0.973
Openness - Total Events	-0.007	0.969
Openness - Total Focus Time	0.023	0.903
Openness - Total Runs	0.080	0.664
Openness - Typing Activity	0.064	0.727

*Significant at $p < 0.05$

Table 17 – Spearman Correlations: Predictors and Academic Performance

Variable Pair	ρ	p**-value**
Distractions and Academic Performance		
External Distractions - Exam 1	-0.087	0.637
External Distractions - Exam 2	-0.078	0.671
External Distractions - Exam 3	0.136	0.458
External Distractions - Final Pass Status	0.007	0.970
External Distractions - GPA	0.026	0.887
Internal Distractions - Exam 1	0.004	0.982

Continued on next page

Table 17 continued

Variable Pair	ρ	p**-value**
Internal Distractions - Exam 2	-0.185	0.311
Internal Distractions - Exam 3	0.006	0.976
Internal Distractions - Final Pass Status	-0.014	0.938
Internal Distractions - GPA	-0.038	0.837
Personality Traits and Academic Performance		
Agreeableness - Exam 1	0.173	0.343
Agreeableness - Exam 2	0.108	0.555
Agreeableness - Exam 3	0.177	0.333
Agreeableness - Final Pass Status	0.205	0.261
Agreeableness - GPA	0.241	0.183
Conscientiousness - Exam 1	0.271	0.134
Conscientiousness - Exam 2	0.273	0.131
Conscientiousness - Exam 3	0.392	0.026*
Conscientiousness - Final Pass Status	0.313	0.081
Conscientiousness - GPA	0.421	0.016*
Extraversion - Exam 1	0.212	0.245
Extraversion - Exam 2	0.020	0.914
Extraversion - Exam 3	0.166	0.363
Extraversion - Final Pass Status	0.046	0.804
Extraversion - GPA	0.240	0.186
Neuroticism - Exam 1	-0.161	0.380
Neuroticism - Exam 2	-0.241	0.184
Neuroticism - Exam 3	-0.019	0.919
Neuroticism - Final Pass Status	-0.109	0.551
Neuroticism - GPA	-0.069	0.706
Openness - Exam 1	0.148	0.420
Openness - Exam 2	0.221	0.223
Openness - Exam 3	0.134	0.465
Openness - Final Pass Status	-0.142	0.438
Openness - GPA	0.146	0.425

*Significant at $p < 0.05$

Table 18 – Spearman Correlations: Early IDE Metrics and Academic Performance

Variable Pair	ρ	p**-value**
Avg Duration Per Exercise		

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Table 18 continued

Variable Pair	ρ	p**-value**
Avg Duration Per Exercise - Exam 1	0.024	0.896
Avg Duration Per Exercise - Exam 2	-0.246	0.174
Avg Duration Per Exercise - Exam 3	-0.116	0.527
Avg Duration Per Exercise - Final Pass Status	-0.126	0.493
Avg Duration Per Exercise - GPA	-0.176	0.335
Avg Events Per Exercise		
Avg Events Per Exercise - Exam 1	0.153	0.404
Avg Events Per Exercise - Exam 2	-0.209	0.251
Avg Events Per Exercise - Exam 3	-0.137	0.454
Avg Events Per Exercise - Final Pass Status	-0.175	0.339
Avg Events Per Exercise - GPA	-0.155	0.398
Avg Time Between Events		
Avg Time Between Events - Exam 1	-0.278	0.123
Avg Time Between Events - Exam 2	-0.223	0.221
Avg Time Between Events - Exam 3	-0.119	0.516
Avg Time Between Events - Final Pass Status	-0.056	0.761
Avg Time Between Events - GPA	-0.184	0.315
Code Correctness		
Code Correctness - Exam 1	0.282	0.118
Code Correctness - Exam 2	0.552	0.001*
Code Correctness - Exam 3	0.472	0.006*
Code Correctness - Final Pass Status	0.359	0.043*
Code Correctness - GPA	0.453	0.009*
Coding Activity Intensity		
Coding Activity Intensity - Exam 1	0.473	0.006*
Coding Activity Intensity - Exam 2	0.444	0.011*
Coding Activity Intensity - Exam 3	0.286	0.113
Coding Activity Intensity - Final Pass Status	0.231	0.204
Coding Activity Intensity - GPA	0.366	0.040*
Submission Frequency		
Submission Frequency - Exam 1	0.224	0.218
Submission Frequency - Exam 2	0.456	0.009*
Submission Frequency - Exam 3	0.655	< 0.001*
Submission Frequency - Final Pass Status	0.210	0.249
Submission Frequency - GPA	0.589	< 0.001*
Success Rates		

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Table 18 continued

Variable Pair	ρ	p-**value**
Success Rates - Exam 1	0.323	0.071
Success Rates - Exam 2	0.496	0.004*
Success Rates - Exam 3	0.475	0.006*
Success Rates - Final Pass Status	0.318	0.076
Success Rates - GPA	0.432	0.014*
Successful Submissions		
Successful Submissions - Exam 1	0.276	0.126
Successful Submissions - Exam 2	0.563	< 0.001*
Successful Submissions - Exam 3	0.698	< 0.001*
Successful Submissions - Final Pass Status	0.331	0.064
Successful Submissions - GPA	0.636	< 0.001*
Total Blur Time		
Total Blur Time - Exam 1	0.302	0.093
Total Blur Time - Exam 2	0.278	0.124
Total Blur Time - Exam 3	0.428	0.015*
Total Blur Time - Final Pass Status	0.241	0.183
Total Blur Time - GPA	0.444	0.011*
Total Deletions		
Total Deletions - Exam 1	0.218	0.231
Total Deletions - Exam 2	0.349	0.050
Total Deletions - Exam 3	0.424	0.016*
Total Deletions - Final Pass Status	0.210	0.249
Total Deletions - GPA	0.454	0.009*
Total Duration		
Total Duration - Exam 1	0.172	0.347
Total Duration - Exam 2	0.161	0.378
Total Duration - Exam 3	0.356	0.045*
Total Duration - Final Pass Status	0.189	0.301
Total Duration - GPA	0.290	0.107
Total Events		
Total Events - Exam 1	0.396	0.025*
Total Events - Exam 2	0.369	0.038*
Total Events - Exam 3	0.462	0.008*
Total Events - Final Pass Status	0.308	0.087
Total Events - GPA	0.464	0.008*
Total Focus Time		

Continued on next page

Table 18 continued

Variable Pair	ρ	p**-value**
Total Focus Time - Exam 1	0.318	0.076
Total Focus Time - Exam 2	0.285	0.114
Total Focus Time - Exam 3	0.431	0.014*
Total Focus Time - Final Pass Status	0.234	0.197
Total Focus Time - GPA	0.443	0.011*
Total Runs		
Total Runs - Exam 1	0.062	0.737
Total Runs - Exam 2	0.138	0.452
Total Runs - Exam 3	0.212	0.244
Total Runs - Final Pass Status	0.091	0.621
Total Runs - GPA	0.276	0.126
Typing Activity		
Typing Activity - Exam 1	0.296	0.100
Typing Activity - Exam 2	0.472	0.006*
Typing Activity - Exam 3	0.589	< 0.001*
Typing Activity - Final Pass Status	0.419	0.017*
Typing Activity - GPA	0.569	< 0.001*

*Significant at $p < 0.05$

Table 19 – Multiple Regression Results - Predictors of IDE Metrics and Academic Performance

Predictor - Outcome	β	p**-value**	R^2
Model: Predictors of Avg Duration Per Exercise			
$N = 32$, Model $R^2 = 0.050$, Adjusted $R^2 = -0.227$			
Agreeableness - Avg Duration Per Exercise	4.241	0.458	0.050
Openness - Avg Duration Per Exercise	-3.189	0.572	
External Distractions - Avg Duration Per Exercise	7.180	0.659	
Conscientiousness - Avg Duration Per Exercise	-2.527	0.663	
Neuroticism - Avg Duration Per Exercise	1.220	0.773	
Internal Distractions - Avg Duration Per Exercise	-2.295	0.878	
Extraversion - Avg Duration Per Exercise	-0.650	0.890	
Model: Predictors of Avg Events Per Exercise			
$N = 32$, Model $R^2 = 0.072$, Adjusted $R^2 = -0.199$			
External Distractions - Avg Events Per Exercise	-395.904	0.411	0.072
Openness - Avg Events Per Exercise	-74.852	0.652	
Conscientiousness - Avg Events Per Exercise	-68.831	0.687	

Continued on next page

Table 19 continued

Predictor - Outcome	β	p-**value**	R^2
Neuroticism - Avg Events Per Exercise	-46.165	0.711	
Agreeableness - Avg Events Per Exercise	36.324	0.828	
Internal Distractions - Avg Events Per Exercise	-72.944	0.868	
Extraversion - Avg Events Per Exercise	17.470	0.899	
Model: Predictors of Coding Activity Intensity			
$N = 32$, Model $R^2 = 0.305$, Adjusted $R^2 = 0.102$			
External Distractions - Coding Activity Intensity	-38.551	0.110	0.305
Neuroticism - Coding Activity Intensity	-7.497	0.228	
Internal Distractions - Coding Activity Intensity	-21.993	0.313	
Conscientiousness - Coding Activity Intensity	7.104	0.399	
Extraversion - Coding Activity Intensity	-4.674	0.492	
Openness - Coding Activity Intensity	3.303	0.685	
Agreeableness - Coding Activity Intensity	-1.314	0.873	
Model: Predictors of Exam 1			
$N = 32$, Model $R^2 = 0.172$, Adjusted $R^2 = -0.069$			
Agreeableness - Exam 1	1.909	0.329	0.172
Neuroticism - Exam 1	-1.127	0.437	
Conscientiousness - Exam 1	1.486	0.453	
Openness - Exam 1	0.563	0.769	
External Distractions - Exam 1	-1.086	0.844	
Extraversion - Exam 1	-0.103	0.949	
Internal Distractions - Exam 1	0.262	0.959	
Model: Predictors of Exam 2			
$N = 32$, Model $R^2 = 0.144$, Adjusted $R^2 = -0.106$			
Conscientiousness - Exam 2	2.909	0.280	0.144
Internal Distractions - Exam 2	-4.672	0.498	
Agreeableness - Exam 2	1.582	0.546	
Neuroticism - Exam 2	-0.920	0.637	
Extraversion - Exam 2	-0.861	0.690	
External Distractions - Exam 2	-1.807	0.809	
Openness - Exam 2	0.191	0.941	
Model: Predictors of Exam 3			
$N = 32$, Model $R^2 = 0.151$, Adjusted $R^2 = -0.096$			
Conscientiousness - Exam 3	3.118	0.235	0.151
External Distractions - Exam 3	6.075	0.406	
Extraversion - Exam 3	1.059	0.614	

Continued on next page

Table 19 continued

Predictor - Outcome	β	p**-value**	R^2
Openness - Exam 3	0.539	0.831	
Agreeableness - Exam 3	0.323	0.899	
Neuroticism - Exam 3	0.209	0.912	
Internal Distractions - Exam 3	-0.121	0.986	
Model: Predictors of GPA			
$N = 32$, Model $R^2 = 0.159$, Adjusted $R^2 = -0.086$			
Conscientiousness - GPA	13.949	0.213	0.159
Agreeableness - GPA	6.997	0.520	
Extraversion - GPA	3.300	0.712	
Neuroticism - GPA	-2.590	0.748	
Openness - GPA	-2.268	0.833	
Internal Distractions - GPA	4.679	0.869	
External Distractions - GPA	-3.592	0.908	
Model: Predictors of Overall Correctness			
$N = 32$, Model $R^2 = 0.303$, Adjusted $R^2 = 0.099$			
Internal Distractions - Overall Correctness	-0.688	0.023*	0.303
Neuroticism - Overall Correctness	0.087	0.289	
Conscientiousness - Overall Correctness	0.101	0.365	
External Distractions - Overall Correctness	0.144	0.643	
Agreeableness - Overall Correctness	-0.036	0.738	
Openness - Overall Correctness	-0.012	0.909	
Extraversion - Overall Correctness	-0.005	0.959	
Model: Predictors of Pause Duration			
$N = 32$, Model $R^2 = 0.169$, Adjusted $R^2 = -0.073$			
Agreeableness - Pause Duration	-2.443	0.242	0.169
Neuroticism - Pause Duration	1.478	0.340	
Internal Distractions - Pause Duration	3.545	0.514	
Extraversion - Pause Duration	0.859	0.614	
External Distractions - Pause Duration	2.239	0.704	
Openness - Pause Duration	-0.496	0.808	
Conscientiousness - Pause Duration	-0.003	0.999	
Model: Predictors of Submission Frequency			
$N = 32$, Model $R^2 = 0.265$, Adjusted $R^2 = 0.050$			
Extraversion - Submission Frequency	6.201	0.068	0.265
Agreeableness - Submission Frequency	4.977	0.218	
Openness - Submission Frequency	1.079	0.784	

Continued on next page

Table 19 continued

Predictor - Outcome	β	p-value	R^2
Conscientiousness - Submission Frequency	-0.685	0.866	
Internal Distractions - Submission Frequency	-1.652	0.874	
External Distractions - Submission Frequency	0.961	0.933	
Neuroticism - Submission Frequency	-0.225	0.939	
Model: Predictors of Success Rates			
$N = 32$, Model $R^2 = 0.354$, Adjusted $R^2 = 0.165$			
Internal Distractions - Success Rates	-0.461	0.017*	0.354
Neuroticism - Success Rates	0.050	0.335	
Extraversion - Success Rates	-0.047	0.411	
Agreeableness - Success Rates	-0.055	0.427	
Conscientiousness - Success Rates	0.053	0.455	
External Distractions - Success Rates	0.034	0.863	
Openness - Success Rates	0.008	0.909	
Model: Predictors of Successful Submissions			
$N = 32$, Model $R^2 = 0.396$, Adjusted $R^2 = 0.220$			
Extraversion - Successful Submissions	1.926	0.046*	0.396
Internal Distractions - Successful Submissions	-4.943	0.103	
Conscientiousness - Successful Submissions	1.784	0.128	
Neuroticism - Successful Submissions	1.257	0.142	
Openness - Successful Submissions	-0.667	0.550	
External Distractions - Successful Submissions	1.851	0.565	
Agreeableness - Successful Submissions	0.207	0.854	
Model: Predictors of Total Blur Time			
$N = 32$, Model $R^2 = 0.165$, Adjusted $R^2 = -0.079$			
External Distractions - Total Blur Time	-82.079	0.198	0.165
Extraversion - Total Blur Time	18.684	0.306	
Conscientiousness - Total Blur Time	21.046	0.350	
Agreeableness - Total Blur Time	-15.009	0.495	
Neuroticism - Total Blur Time	-10.881	0.507	
Openness - Total Blur Time	-14.203	0.515	
Internal Distractions - Total Blur Time	8.789	0.879	
Model: Predictors of Total Deletions			
$N = 32$, Model $R^2 = 0.244$, Adjusted $R^2 = 0.024$			
External Distractions - Total Deletions	-462.235	0.055	0.244
Conscientiousness - Total Deletions	76.135	0.360	
Extraversion - Total Deletions	48.923	0.466	

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Table 19 continued

Predictor - Outcome	β	p-value	R^2
Agreeableness - Total Deletions	11.984	0.882	
Openness - Total Deletions	4.197	0.958	
Neuroticism - Total Deletions	-1.496	0.980	
Internal Distractions - Total Deletions	-1.802	0.993	
Model: Predictors of Total Duration			
$N = 32$, Model $R^2 = 0.122$, Adjusted $R^2 = -0.134$			
Agreeableness - Total Duration	35.408	0.236	0.122
Openness - Total Duration	-23.896	0.416	
External Distractions - Total Duration	51.899	0.539	
Internal Distractions - Total Duration	-33.507	0.665	
Extraversion - Total Duration	10.362	0.670	
Conscientiousness - Total Duration	9.627	0.748	
Neuroticism - Total Duration	6.275	0.775	
Model: Predictors of Total Events			
$N = 32$, Model $R^2 = 0.275$, Adjusted $R^2 = 0.064$			
External Distractions - Total Events	-3135.687	0.149	0.275
Conscientiousness - Total Events	1068.622	0.167	
Extraversion - Total Events	835.516	0.181	
Neuroticism - Total Events	-216.071	0.697	
Internal Distractions - Total Events	-736.472	0.706	
Openness - Total Events	-272.523	0.712	
Agreeableness - Total Events	-120.256	0.872	
Model: Predictors of Total Focus Time			
$N = 32$, Model $R^2 = 0.173$, Adjusted $R^2 = -0.068$			
External Distractions - Total Focus Time	-85.444	0.214	0.173
Extraversion - Total Focus Time	21.665	0.273	
Conscientiousness - Total Focus Time	22.309	0.359	
Neuroticism - Total Focus Time	-12.371	0.485	
Openness - Total Focus Time	-16.335	0.488	
Agreeableness - Total Focus Time	-13.188	0.579	
Internal Distractions - Total Focus Time	2.975	0.962	
Model: Predictors of Total Runs			
$N = 32$, Model $R^2 = 0.053$, Adjusted $R^2 = -0.223$			
Internal Distractions - Total Runs	34.485	0.353	0.053
Openness - Total Runs	9.561	0.493	
Agreeableness - Total Runs	-8.327	0.554	

Continued on next page

Table 19 continued

Predictor - Outcome	β	p-value	R^2
External Distractions - Total Runs	-15.592	0.697	
Extraversion - Total Runs	2.458	0.832	
Conscientiousness - Total Runs	0.473	0.974	
Neuroticism - Total Runs	-0.010	0.999	
Model: Predictors of Typing Activity			
$N = 32$, Model $R^2 = 0.454$, Adjusted $R^2 = 0.294$			
Extraversion - Typing Activity	574.476	0.042*	0.454
Conscientiousness - Typing Activity	682.742	0.050*	
External Distractions - Typing Activity	-1806.703	0.063	
Openness - Typing Activity	123.513	0.704	
Internal Distractions - Typing Activity	-299.164	0.728	
Agreeableness - Typing Activity	-100.953	0.758	
Neuroticism - Typing Activity	-17.865	0.942	

*Significant at $p < 0.05$

Table 20 – Multiple Regression Moderation Results - Interaction Terms

Interaction Term	**Interaction** β	p-**value**	**Raw Sig.**
Model Outcome: Avg Duration Per Exercise			
$N = 32$, Model $R^2 = 0.049$, Adj. $R^2 = -0.053$, Model F-test $p = 0.701$			
Internal Distractions × Neuroticism	-24.902	0.287	
Internal Distractions × Conscientiousness	18.173	0.422	
External Distractions × Openness	13.852	0.464	
Internal Distractions × Openness	-11.770	0.576	
Internal Distractions × Agreeableness	-15.901	0.588	
External Distractions × Neuroticism	9.926	0.637	
External Distractions × Extraversion	2.655	0.878	
Internal Distractions × Extraversion	-2.522	0.907	
External Distractions × Conscientiousness	2.275	0.919	
External Distractions × Agreeableness	-0.657	0.980	
Model Outcome: Avg Events Per Exercise			
$N = 32$, Model $R^2 = 0.086$, Adj. $R^2 = -0.012$, Model F-test $p = 0.463$			
External Distractions × Openness	521.343	0.345	
External Distractions × Agreeableness	711.443	0.356	
External Distractions × Conscientiousness	531.882	0.413	
Internal Distractions × Extraversion	476.049	0.460	

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
Internal Distractions × Neuroticism	-481.295	0.489	
Internal Distractions × Openness	-298.963	0.636	
Internal Distractions × Conscientiousness	251.014	0.710	
External Distractions × Neuroticism	-194.014	0.752	
Internal Distractions × Agreeableness	237.606	0.786	
External Distractions × Extraversion	26.387	0.958	
Model Outcome: Coding Activity Intensity			
$N = 32$, Model $R^2 = 0.276$, Adj. $R^2 = 0.199$, Model F-test $p = 0.027$			
Internal Distractions × Neuroticism	63.653	0.070	
External Distractions × Extraversion	-25.517	0.336	
External Distractions × Openness	-27.212	0.349	
Internal Distractions × Conscientiousness	-30.568	0.395	
Internal Distractions × Openness	24.586	0.461	
Internal Distractions × Extraversion	20.798	0.547	
External Distractions × Agreeableness	23.758	0.563	
Internal Distractions × Agreeableness	-22.477	0.628	
External Distractions × Neuroticism	-6.520	0.838	
External Distractions × Conscientiousness	6.208	0.856	
Model Outcome: Exam 1			
$N = 32$, Model $R^2 = 0.120$, Adj. $R^2 = 0.025$, Model F-test $p = 0.304$			
Internal Distractions × Extraversion	13.273	0.083	
Internal Distractions × Neuroticism	9.324	0.265	
Internal Distractions × Agreeableness	8.988	0.369	
External Distractions × Neuroticism	4.741	0.529	
External Distractions × Conscientiousness	4.858	0.535	
External Distractions × Openness	3.586	0.600	
External Distractions × Extraversion	-2.903	0.641	
Internal Distractions × Conscientiousness	-2.730	0.734	
External Distractions × Agreeableness	1.497	0.869	
Internal Distractions × Openness	-0.740	0.923	
Model Outcome: Exam 2			
$N = 32$, Model $R^2 = 0.101$, Adj. $R^2 = 0.005$, Model F-test $p = 0.387$			
Internal Distractions × Neuroticism	15.089	0.173	
External Distractions × Agreeableness	-13.543	0.277	
Internal Distractions × Extraversion	11.192	0.277	
External Distractions × Openness	-9.611	0.289	

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Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
External Distractions × Conscientiousness	-7.226	0.483	
External Distractions × Neuroticism	5.214	0.606	
Internal Distractions × Conscientiousness	-4.897	0.640	
Internal Distractions × Openness	2.703	0.789	
External Distractions × Extraversion	-1.463	0.861	
Internal Distractions × Agreeableness	0.322	0.981	
Model Outcome: Exam 3			
$N = 32$, Model $R^2 = 0.232$, Adj. $R^2 = 0.150$, Model F-test $p = 0.057$			
Internal Distractions × Conscientiousness	-19.526	0.047	*
External Distractions × Openness	-12.769	0.140	
External Distractions × Agreeableness	-16.432	0.172	
Internal Distractions × Neuroticism	13.748	0.214	
External Distractions × Conscientiousness	-10.264	0.296	
External Distractions × Extraversion	-7.760	0.324	
Internal Distractions × Openness	-6.335	0.525	
External Distractions × Neuroticism	3.726	0.706	
Internal Distractions × Agreeableness	-3.001	0.828	
Internal Distractions × Extraversion	0.411	0.968	
Model Outcome: GPA			
$N = 32$, Model $R^2 = 0.118$, Adj. $R^2 = 0.024$, Model F-test $p = 0.311$			
Internal Distractions × Neuroticism	82.303	0.076	
Internal Distractions × Conscientiousness	-65.160	0.126	
External Distractions × Openness	-36.802	0.338	
Internal Distractions × Extraversion	36.009	0.402	
External Distractions × Agreeableness	-35.539	0.489	
External Distractions × Extraversion	-21.622	0.529	
External Distractions × Neuroticism	21.920	0.607	
External Distractions × Conscientiousness	-16.699	0.697	
Internal Distractions × Openness	-10.860	0.800	
Internal Distractions × Agreeableness	8.359	0.884	
Model Outcome: Overall Correctness			
$N = 32$, Model $R^2 = 0.279$, Adj. $R^2 = 0.202$, Model F-test $p = 0.025$			
Internal Distractions × Conscientiousness	-0.590	0.180	
Internal Distractions × Openness	-0.403	0.338	
External Distractions × Openness	-0.366	0.388	
External Distractions × Extraversion	-0.326	0.396	

Continued on next page

Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
External Distractions × Agreeableness	-0.490	0.400	
Internal Distractions × Agreeableness	-0.470	0.420	
External Distractions × Neuroticism	-0.291	0.530	
Internal Distractions × Neuroticism	0.103	0.820	
External Distractions × Conscientiousness	-0.087	0.860	
Internal Distractions × Extraversion	-0.049	0.909	
Model Outcome: Success Rates			
$N = 32$, Model $R^2 = 0.318$, Adj. $R^2 = 0.244$, Model F-test $p = 0.012$			
Internal Distractions × Extraversion	0.340	0.207	
Internal Distractions × Agreeableness	0.372	0.311	
External Distractions × Neuroticism	-0.187	0.543	
Internal Distractions × Openness	-0.116	0.671	
External Distractions × Extraversion	-0.098	0.697	
Internal Distractions × Conscientiousness	0.106	0.717	
External Distractions × Openness	-0.097	0.732	
External Distractions × Agreeableness	-0.104	0.782	
External Distractions × Conscientiousness	-0.032	0.924	
Internal Distractions × Neuroticism	-0.021	0.943	
Model Outcome: Successful Submissions			
$N = 32$, Model $R^2 = 0.286$, Adj. $R^2 = 0.209$, Model F-test $p = 0.023$			
External Distractions × Openness	-12.859	0.003	*
Internal Distractions × Conscientiousness	-10.731	0.026	*
Internal Distractions × Agreeableness	-12.865	0.056	
Internal Distractions × Extraversion	-7.157	0.128	
External Distractions × Agreeableness	-8.429	0.191	
Internal Distractions × Neuroticism	4.006	0.464	
External Distractions × Neuroticism	-3.376	0.510	
External Distractions × Extraversion	-2.229	0.568	
Internal Distractions × Openness	2.278	0.654	
External Distractions × Conscientiousness	-1.999	0.695	
Model Outcome: Total Blur Time			
$N = 32$, Model $R^2 = 0.133$, Adj. $R^2 = 0.040$, Model F-test $p = 0.256$			
Internal Distractions × Conscientiousness	-162.987	0.071	
Internal Distractions × Agreeableness	-168.194	0.156	
External Distractions × Openness	-96.284	0.200	
Internal Distractions × Extraversion	-94.197	0.273	

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Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
External Distractions × Neuroticism	88.373	0.286	
Internal Distractions × Openness	61.615	0.478	
External Distractions × Conscientiousness	37.117	0.675	
External Distractions × Agreeableness	-39.556	0.709	
External Distractions × Extraversion	-21.277	0.752	
Internal Distractions × Neuroticism	-8.205	0.932	
Model Outcome: Total Deletions			
$N = 32$, Model $R^2 = 0.249$, Adj. $R^2 = 0.168$, Model F-test $p = 0.043$			
Internal Distractions × Conscientiousness	-840.584	0.012	*
Internal Distractions × Agreeableness	-880.177	0.044	*
External Distractions × Openness	-495.847	0.067	
External Distractions × Extraversion	-378.601	0.118	
Internal Distractions × Extraversion	-277.136	0.408	
External Distractions × Agreeableness	-257.033	0.503	
External Distractions × Conscientiousness	-172.391	0.586	
Internal Distractions × Openness	-176.649	0.596	
External Distractions × Neuroticism	87.627	0.777	
Internal Distractions × Neuroticism	8.902	0.981	
Model Outcome: Total Duration			
$N = 32$, Model $R^2 = 0.197$, Adj. $R^2 = 0.111$, Model F-test $p = 0.100$			
Internal Distractions × Agreeableness	-307.943	0.038	*
External Distractions × Agreeableness	-193.815	0.152	
Internal Distractions × Extraversion	-148.391	0.194	
External Distractions × Neuroticism	132.050	0.239	
Internal Distractions × Conscientiousness	-122.166	0.310	
External Distractions × Openness	-74.193	0.469	
Internal Distractions × Neuroticism	-74.174	0.560	
External Distractions × Conscientiousness	-58.856	0.621	
External Distractions × Extraversion	-18.152	0.843	
Internal Distractions × Openness	-11.162	0.922	
Model Outcome: Total Events			
$N = 32$, Model $R^2 = 0.335$, Adj. $R^2 = 0.264$, Model F-test $p = 0.009$			
Internal Distractions × Conscientiousness	-8384.862	0.005	*
External Distractions × Openness	-5649.876	0.031	*
Internal Distractions × Agreeableness	-7857.307	0.055	
External Distractions × Extraversion	-3296.481	0.150	

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
External Distractions × Agreeableness	-4428.557	0.235	
Internal Distractions × Extraversion	-3280.527	0.272	
External Distractions × Conscientiousness	-2112.397	0.483	
External Distractions × Neuroticism	1559.809	0.603	
Internal Distractions × Neuroticism	-592.258	0.864	
Internal Distractions × Openness	-65.306	0.983	
Model Outcome: Total Focus Time			
$N = 32$, Model $R^2 = 0.123$, Adj. $R^2 = 0.029$, Model F-test $p = 0.290$			
Internal Distractions × Conscientiousness	-165.166	0.093	
Internal Distractions × Agreeableness	-178.012	0.166	
External Distractions × Openness	-104.188	0.202	
External Distractions × Neuroticism	93.756	0.296	
Internal Distractions × Extraversion	-86.770	0.351	
Internal Distractions × Openness	61.615	0.489	
External Distractions × Agreeableness	-49.395	0.667	
External Distractions × Conscientiousness	35.085	0.715	
External Distractions × Extraversion	-23.766	0.743	
Internal Distractions × Neuroticism	-5.623	0.957	
Model Outcome: Total Runs			
$N = 32$, Model $R^2 = 0.169$, Adj. $R^2 = 0.079$, Model F-test $p = 0.154$			
External Distractions × Neuroticism	112.033	0.025	*
Internal Distractions × Conscientiousness	-77.095	0.162	
Internal Distractions × Extraversion	-68.569	0.191	
Internal Distractions × Agreeableness	-79.769	0.264	
External Distractions × Agreeableness	-52.087	0.426	
External Distractions × Conscientiousness	33.973	0.540	
External Distractions × Openness	-27.083	0.565	
Internal Distractions × Openness	19.235	0.710	
Internal Distractions × Neuroticism	15.772	0.786	
External Distractions × Extraversion	-4.543	0.915	
Model Outcome: Typing Activity			
$N = 32$, Model $R^2 = 0.481$, Adj. $R^2 = 0.425$, Model F-test $p =< 0.001$			
Internal Distractions × Conscientiousness	-4662.189	< 0.001	*
External Distractions × Openness	-3606.773	0.003	*
External Distractions × Extraversion	-2063.348	0.051	
Internal Distractions × Agreeableness	-3323.370	0.103	

Continued on next page

Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
External Distractions × Agreeableness	-2606.462	0.155	
External Distractions × Conscientiousness	-1935.639	0.161	
Internal Distractions × Extraversion	-1743.145	0.218	
External Distractions × Neuroticism	-337.832	0.823	
Internal Distractions × Neuroticism	-266.912	0.879	
Internal Distractions × Openness	-184.540	0.903	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.199$, Adj. $R^2 = 0.113$, Model F-test $p = 0.098$			
External Distractions × Openness	-32.243	0.025	*
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.184$, Adj. $R^2 = 0.097$, Model F-test $p = 0.122$			
Internal Distractions × Conscientiousness	-37.170	0.030	*
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.277$, Adj. $R^2 = 0.199$, Model F-test $p = 0.026$			
Internal Distractions × Agreeableness	-44.902	0.031	*
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.170$, Adj. $R^2 = 0.081$, Model F-test $p = 0.150$			
External Distractions × Agreeableness	-20.301	0.298	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.138$, Adj. $R^2 = 0.045$, Model F-test $p = 0.239$			
External Distractions × Agreeableness	-9.807	0.311	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.225$, Adj. $R^2 = 0.142$, Model F-test $p = 0.064$			
Internal Distractions × Extraversion	-15.202	0.323	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.061$, Adj. $R^2 = -0.039$, Model F-test $p = 0.614$			
Internal Distractions × Openness	-7.144	0.376	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.043$, Adj. $R^2 = -0.060$, Model F-test $p = 0.744$			
Internal Distractions × Extraversion	-7.265	0.382	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.079$, Adj. $R^2 = -0.020$, Model F-test $p = 0.506$			
External Distractions × Conscientiousness	-6.730	0.425	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.097$, Adj. $R^2 = 0.000$, Model F-test $p = 0.407$			
Internal Distractions × Neuroticism	-5.585	0.524	

Continued on next page

Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.057$, Adj. $R^2 = -0.044$, Model F-test $p = 0.644$			
External Distractions × Extraversion	-3.936	0.548	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.107$, Adj. $R^2 = 0.011$, Model F-test $p = 0.359$			
External Distractions × Neuroticism	4.500	0.564	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.121$, Adj. $R^2 = 0.027$, Model F-test $p = 0.299$			
Internal Distractions × Agreeableness	-4.869	0.651	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.026$, Adj. $R^2 = -0.079$, Model F-test $p = 0.864$			
External Distractions × Neuroticism	7.243	0.664	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.064$, Adj. $R^2 = -0.036$, Model F-test $p = 0.597$			
External Distractions × Openness	-2.585	0.720	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.040$, Adj. $R^2 = -0.062$, Model F-test $p = 0.759$			
Internal Distractions × Openness	5.654	0.734	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.027$, Adj. $R^2 = -0.078$, Model F-test $p = 0.856$			
Internal Distractions × Conscientiousness	2.836	0.746	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.044$, Adj. $R^2 = -0.059$, Model F-test $p = 0.735$			
External Distractions × Conscientiousness	-5.579	0.751	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.198$, Adj. $R^2 = 0.112$, Model F-test $p = 0.099$			
External Distractions × Extraversion	1.239	0.920	
Model Outcome: nan			
$N = 32$, Model $R^2 = 0.018$, Adj. $R^2 = -0.088$, Model F-test $p = 0.918$			
Internal Distractions × Neuroticism	-0.318	0.986	

Sig. = Significance ($p < 0.05$)

APPENDIX C

Class 2 Complete Tables

Table 21 – Spearman Correlations: Personality Traits and Distractions

Variable Pair	ρ	p**-value**
Personality Traits Correlated with Predictors		
Agreeableness - Conscientiousness	0.090	0.618
Distractions Correlated with Predictors		
External Distractions - Extraversion	-0.453	0.008*
External Distractions - Neuroticism	0.175	0.329
External Distractions - Openness	-0.165	0.360
External Distractions - Agreeableness	-0.134	0.458
External Distractions - Conscientiousness	-0.046	0.798
Personality Traits Correlated with Predictors		
Extraversion - Agreeableness	0.460	0.007*
Extraversion - Conscientiousness	-0.131	0.467
Extraversion - Openness	0.023	0.901
Distractions Correlated with Predictors		
Internal Distractions - External Distractions	0.449	0.009*
Internal Distractions - Conscientiousness	-0.288	0.104
Internal Distractions - Openness	-0.261	0.142
Internal Distractions - Agreeableness	-0.181	0.315
Internal Distractions - Extraversion	-0.176	0.326
Internal Distractions - Neuroticism	0.004	0.984
Personality Traits Correlated with Predictors		
Neuroticism - Extraversion	-0.450	0.009*
Neuroticism - Agreeableness	-0.405	0.019*
Neuroticism - Conscientiousness	0.100	0.579

Continued on next page

Table 21 continued

Variable Pair	ρ	p**-value**
Neuroticism - Openness	0.016	0.932
Personality Traits Correlated with Predictors		
Openness - Conscientiousness	0.421	0.015*
Openness - Agreeableness	0.227	0.204

*Significant at $p < 0.05$

Table 22 – Spearman Correlations: Distractions, Personality Traits, and IDE Metrics

Variable Pair	ρ	p**-value**
Internal Distractions and IDE Metrics		
Internal Distractions - Success Rates	0.419	0.015*
Internal Distractions - Code Correctness	0.396	0.023*
Internal Distractions - Avg Duration Per Exercise	0.343	0.050
Internal Distractions - Avg Events Per Exercise	0.254	0.153
Internal Distractions - Pause Duration	-0.239	0.181
Internal Distractions - Total Deletions	-0.232	0.194
Internal Distractions - Submission Frequency	-0.231	0.197
Internal Distractions - Coding Activity Intensity	-0.178	0.321
Internal Distractions - Total Focus Time	0.174	0.333
Internal Distractions - Total Blur Time	0.165	0.358
Internal Distractions - Typing Activity	-0.148	0.411
Internal Distractions - Successful Submissions	-0.088	0.626
Internal Distractions - Total Events	-0.031	0.863
Internal Distractions - Total Runs	-0.028	0.876
Internal Distractions - Total Duration	0.020	0.913
External Distractions and IDE Metrics		
External Distractions - Success Rates	0.419	0.015*
External Distractions - Code Correctness	0.400	0.021*
External Distractions - Avg Duration Per Exercise	0.351	0.045*
External Distractions - Submission Frequency	-0.298	0.092
External Distractions - Avg Events Per Exercise	0.229	0.199
External Distractions - Coding Activity Intensity	-0.150	0.404
External Distractions - Typing Activity	-0.125	0.489
External Distractions - Total Deletions	-0.090	0.618
External Distractions - Pause Duration	-0.082	0.648
External Distractions - Successful Submissions	-0.067	0.709

Continued on next page

Table 22 continued

Variable Pair	ρ	p-value
External Distractions - Total Blur Time	0.066	0.716
External Distractions - Total Focus Time	0.051	0.777
External Distractions - Total Duration	0.039	0.831
External Distractions - Total Events	-0.006	0.975
External Distractions - Total Runs	-0.005	0.976
Personality Traits and IDE Metrics		
Agreeableness - Submission Frequency	-0.313	0.076
Agreeableness - Successful Submissions	-0.255	0.153
Agreeableness - Total Duration	-0.228	0.202
Agreeableness - Total Deletions	-0.205	0.253
Agreeableness - Avg Events Per Exercise	-0.200	0.265
Agreeableness - Total Events	-0.191	0.286
Agreeableness - Coding Activity Intensity	-0.189	0.292
Agreeableness - Success Rates	0.177	0.323
Agreeableness - Pause Duration	0.151	0.401
Agreeableness - Typing Activity	-0.143	0.427
Agreeableness - Code Correctness	0.140	0.439
Agreeableness - Total Blur Time	-0.127	0.482
Agreeableness - Total Runs	-0.115	0.523
Agreeableness - Total Focus Time	-0.114	0.527
Agreeableness - Avg Duration Per Exercise	-0.093	0.606
Conscientiousness - Avg Events Per Exercise	-0.500	0.003*
Conscientiousness - Pause Duration	0.351	0.045*
Conscientiousness - Total Runs	-0.307	0.082
Conscientiousness - Total Blur Time	-0.299	0.091
Conscientiousness - Coding Activity Intensity	-0.291	0.101
Conscientiousness - Total Focus Time	-0.287	0.105
Conscientiousness - Total Events	-0.282	0.112
Conscientiousness - Total Deletions	-0.201	0.261
Conscientiousness - Typing Activity	-0.165	0.359
Conscientiousness - Avg Duration Per Exercise	-0.144	0.423
Conscientiousness - Total Duration	-0.109	0.544
Conscientiousness - Successful Submissions	0.058	0.746
Conscientiousness - Submission Frequency	0.057	0.755
Conscientiousness - Success Rates	-0.044	0.807
Conscientiousness - Code Correctness	-0.042	0.814

Continued on next page

Table 22 continued

Variable Pair	ρ	p**-value**
Extraversion - Success Rates	-0.360	0.040*
Extraversion - Code Correctness	-0.351	0.045*
Extraversion - Submission Frequency	0.169	0.347
Extraversion - Total Deletions	0.137	0.448
Extraversion - Avg Events Per Exercise	0.134	0.458
Extraversion - Typing Activity	0.115	0.524
Extraversion - Pause Duration	0.089	0.622
Extraversion - Total Events	0.075	0.678
Extraversion - Coding Activity Intensity	0.069	0.702
Extraversion - Total Duration	-0.063	0.728
Extraversion - Total Focus Time	0.062	0.733
Extraversion - Avg Duration Per Exercise	-0.050	0.782
Extraversion - Total Blur Time	0.046	0.801
Extraversion - Total Runs	-0.042	0.815
Extraversion - Successful Submissions	0.040	0.825
Neuroticism - Avg Events Per Exercise	0.167	0.353
Neuroticism - Submission Frequency	0.145	0.421
Neuroticism - Total Duration	0.115	0.525
Neuroticism - Total Events	0.095	0.598
Neuroticism - Success Rates	-0.059	0.746
Neuroticism - Coding Activity Intensity	-0.056	0.756
Neuroticism - Avg Duration Per Exercise	0.039	0.830
Neuroticism - Successful Submissions	0.034	0.850
Neuroticism - Total Runs	-0.029	0.874
Neuroticism - Total Deletions	-0.013	0.943
Neuroticism - Total Focus Time	-0.012	0.946
Neuroticism - Pause Duration	0.012	0.946
Neuroticism - Code Correctness	-0.010	0.955
Neuroticism - Total Blur Time	-0.007	0.968
Neuroticism - Typing Activity	0.006	0.975
Openness - Pause Duration	0.503	0.003*
Openness - Avg Events Per Exercise	-0.489	0.004*
Openness - Total Blur Time	-0.326	0.064
Openness - Total Focus Time	-0.315	0.074
Openness - Total Deletions	-0.305	0.084
Openness - Total Events	-0.280	0.115

Continued on next page

Table 22 continued

Variable Pair	ρ	p**-value**
Openness - Avg Duration Per Exercise	-0.272	0.126
Openness - Typing Activity	-0.243	0.174
Openness - Total Duration	-0.211	0.239
Openness - Code Correctness	-0.196	0.274
Openness - Successful Submissions	-0.168	0.349
Openness - Success Rates	-0.096	0.594
Openness - Coding Activity Intensity	-0.092	0.609
Openness - Total Runs	0.046	0.799
Openness - Submission Frequency	-0.001	0.996

*Significant at $p < 0.05$

Table 23 – Spearman Correlations: Predictors and Academic Performance

Variable Pair	ρ	p**-value**
Distractions and Academic Performance		
External Distractions - Exam 3	-0.196	0.273
External Distractions - Exam 2	0.118	0.511
External Distractions - Final Pass Status	-0.110	0.542
External Distractions - Exam 1	0.062	0.732
External Distractions - GPA	-0.017	0.926
Internal Distractions - Exam 3	-0.278	0.118
Internal Distractions - Final Pass Status	-0.202	0.260
Internal Distractions - GPA	-0.133	0.461
Internal Distractions - Exam 2	-0.087	0.632
Internal Distractions - Exam 1	-0.048	0.789
Personality Traits and Academic Performance		
Agreeableness - Exam 1	0.282	0.112
Agreeableness - Exam 2	-0.071	0.694
Agreeableness - GPA	0.062	0.732
Agreeableness - Exam 3	0.006	0.972
Agreeableness - Final Pass Status	0.003	0.986
Conscientiousness - Exam 1	0.181	0.314
Conscientiousness - Exam 3	0.146	0.417
Conscientiousness - Final Pass Status	0.146	0.418
Conscientiousness - GPA	0.122	0.497
Conscientiousness - Exam 2	-0.013	0.942

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Table 23 continued

Variable Pair	ρ	p**-value**
Extraversion - Exam 3	0.160	0.373
Extraversion - GPA	0.111	0.538
Extraversion - Exam 1	0.037	0.840
Extraversion - Exam 2	-0.032	0.859
Extraversion - Final Pass Status	-0.006	0.972
Neuroticism - Final Pass Status	0.230	0.198
Neuroticism - Exam 3	0.227	0.203
Neuroticism - GPA	0.136	0.451
Neuroticism - Exam 1	-0.132	0.463
Neuroticism - Exam 2	0.125	0.488
Openness - Exam 1	0.529	0.002*
Openness - GPA	0.328	0.062
Openness - Exam 3	0.270	0.128
Openness - Final Pass Status	0.149	0.407
Openness - Exam 2	0.071	0.694

*Significant at $p < 0.05$

Table 24 – Spearman Correlations: Early IDE Metrics and Academic Performance

Variable Pair	ρ	p**-value**
Total Duration		
Total Duration - GPA	0.554	< 0.001*
Total Duration - Final Pass Status	0.502	0.003*
Total Duration - Exam 2	0.496	0.003*
Total Duration - Exam 3	0.470	0.006*
Total Duration - Exam 1	0.277	0.118
Avg Duration Per Exercise		
Avg Duration Per Exercise - Exam 2	0.086	0.635
Avg Duration Per Exercise - Exam 3	-0.028	0.879
Avg Duration Per Exercise - Final Pass Status	0.026	0.887
Avg Duration Per Exercise - GPA	0.018	0.921
Avg Duration Per Exercise - Exam 1	-0.017	0.923
Total Events		
Total Events - GPA	0.557	< 0.001*
Total Events - Final Pass Status	0.522	0.002*
Total Events - Exam 3	0.519	0.002*

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Table 24 continued

Variable Pair	ρ	p-**value**
Total Events - Exam 2	0.511	0.002*
Total Events - Exam 1	0.216	0.226
Avg Events Per Exercise		
Avg Events Per Exercise - Exam 1	-0.256	0.150
Avg Events Per Exercise - Exam 3	0.115	0.523
Avg Events Per Exercise - Exam 2	0.099	0.584
Avg Events Per Exercise - Final Pass Status	0.097	0.593
Avg Events Per Exercise - GPA	0.020	0.912
Total Runs		
Total Runs - Exam 3	0.256	0.151
Total Runs - GPA	0.184	0.306
Total Runs - Exam 2	0.174	0.334
Total Runs - Exam 1	0.137	0.446
Total Runs - Final Pass Status	0.074	0.682
Submission Frequency		
Submission Frequency - Exam 3	0.498	0.003*
Submission Frequency - Final Pass Status	0.422	0.014*
Submission Frequency - GPA	0.412	0.017*
Submission Frequency - Exam 2	0.229	0.199
Submission Frequency - Exam 1	0.019	0.916
Successful Submissions		
Successful Submissions - GPA	0.592	< 0.001*
Successful Submissions - Final Pass Status	0.544	0.001*
Successful Submissions - Exam 3	0.531	0.001*
Successful Submissions - Exam 2	0.448	0.009*
Successful Submissions - Exam 1	0.237	0.184
Success Rates		
Success Rates - Exam 1	0.319	0.070
Success Rates - Exam 2	0.244	0.170
Success Rates - GPA	0.118	0.514
Success Rates - Exam 3	-0.103	0.568
Success Rates - Final Pass Status	0.035	0.845
Code Correctness		
Code Correctness - Exam 1	0.253	0.156
Code Correctness - Exam 2	0.152	0.397
Code Correctness - Exam 3	-0.127	0.483

Continued on next page

Table 24 continued

Variable Pair	ρ	p-**value**
Code Correctness - GPA	0.096	0.593
Code Correctness - Final Pass Status	0.093	0.605
Total Focus Time		
Total Focus Time - Exam 3	0.368	0.035*
Total Focus Time - GPA	0.351	0.045*
Total Focus Time - Final Pass Status	0.309	0.080
Total Focus Time - Exam 2	0.295	0.095
Total Focus Time - Exam 1	0.060	0.740
Total Blur Time		
Total Blur Time - Exam 3	0.353	0.044*
Total Blur Time - GPA	0.344	0.050*
Total Blur Time - Final Pass Status	0.312	0.077
Total Blur Time - Exam 2	0.294	0.097
Total Blur Time - Exam 1	0.058	0.750
Typing Activity		
Typing Activity - GPA	0.598	< 0.001*
Typing Activity - Final Pass Status	0.567	< 0.001*
Typing Activity - Exam 3	0.538	0.001*
Typing Activity - Exam 2	0.425	0.014*
Typing Activity - Exam 1	0.237	0.183
Total Deletions		
Total Deletions - GPA	0.483	0.004*
Total Deletions - Exam 3	0.474	0.005*
Total Deletions - Final Pass Status	0.473	0.005*
Total Deletions - Exam 2	0.450	0.009*
Total Deletions - Exam 1	0.158	0.380
Coding Activity Intensity		
Coding Activity Intensity - Exam 3	0.334	0.057
Coding Activity Intensity - GPA	0.276	0.120
Coding Activity Intensity - Exam 2	0.270	0.128
Coding Activity Intensity - Final Pass Status	0.251	0.159
Coding Activity Intensity - Exam 1	-0.050	0.784
Pause Duration		
Pause Duration - Final Pass Status	-0.193	0.281
Pause Duration - Exam 1	0.158	0.380
Pause Duration - Exam 3	-0.099	0.585

Continued on next page

Table 24 continued

Variable Pair	ρ	p**-value**
Pause Duration - GPA	-0.078	0.666
Pause Duration - Exam 2	-0.068	0.705

*Significant at $p < 0.05$

Table 25 – Multiple Regression Results

Predictor - Outcome	β	p**-value**	R^2
Model: Predictors of Avg Duration Per Exercise			
$N = 33$, Model $R^2 = 0.224$, Adjusted $R^2 = 0.007$			
External Distractions - Avg Duration Per Exercise	16.573	0.250	0.224
Internal Distractions - Avg Duration Per Exercise	13.680	0.256	
Neuroticism - Avg Duration Per Exercise	3.649	0.392	
Extraversion - Avg Duration Per Exercise	0.925	0.779	
Openness - Avg Duration Per Exercise	0.359	0.912	
Conscientiousness - Avg Duration Per Exercise	-0.260	0.940	
Agreeableness - Avg Duration Per Exercise	0.068	0.984	
Model: Predictors of Avg Events Per Exercise			
$N = 33$, Model $R^2 = 0.435$, Adjusted $R^2 = 0.277$			
Conscientiousness - Avg Events Per Exercise	-87.750	0.067	0.435
Extraversion - Avg Events Per Exercise	77.604	0.088	
Neuroticism - Avg Events Per Exercise	87.341	0.132	
External Distractions - Avg Events Per Exercise	293.170	0.132	
Openness - Avg Events Per Exercise	-55.535	0.209	
Agreeableness - Avg Events Per Exercise	-34.448	0.453	
Internal Distractions - Avg Events Per Exercise	-49.639	0.755	
Model: Predictors of Coding Activity Intensity			
$N = 33$, Model $R^2 = 0.217$, Adjusted $R^2 = -0.002$			
Agreeableness - Coding Activity Intensity	-144.487	0.060	0.217
Internal Distractions - Coding Activity Intensity	-263.493	0.312	
Neuroticism - Coding Activity Intensity	-90.477	0.330	
Extraversion - Coding Activity Intensity	-56.133	0.436	
Conscientiousness - Coding Activity Intensity	-46.895	0.534	
Openness - Coding Activity Intensity	40.956	0.563	
External Distractions - Coding Activity Intensity	71.253	0.818	
Model: Predictors of Exam 1			
$N = 33$, Model $R^2 = 0.321$, Adjusted $R^2 = 0.131$			
Openness - Exam 1	3.304	0.023*	0.321

Continued on next page

Table 25 continued

Predictor - Outcome	β	p**-value**	R^2
Agreeableness - Exam 1	1.569	0.284	
Neuroticism - Exam 1	-1.372	0.447	
External Distractions - Exam 1	2.977	0.622	
Conscientiousness - Exam 1	0.506	0.731	
Extraversion - Exam 1	-0.288	0.837	
Internal Distractions - Exam 1	0.687	0.892	
Model: Predictors of Exam 2			
$N = 33$, Model $R^2 = 0.058$, Adjusted $R^2 = -0.205$			
Internal Distractions - Exam 2	-4.211	0.458	0.058
Conscientiousness - Exam 2	-1.094	0.507	
External Distractions - Exam 2	3.596	0.595	
Extraversion - Exam 2	-0.763	0.627	
Agreeableness - Exam 2	0.591	0.715	
Openness - Exam 2	0.500	0.746	
Neuroticism - Exam 2	0.188	0.925	
Model: Predictors of Exam 3			
$N = 33$, Model $R^2 = 0.266$, Adjusted $R^2 = 0.060$			
Neuroticism - Exam 3	3.420	0.077	0.266
Extraversion - Exam 3	2.271	0.128	
Openness - Exam 3	1.699	0.243	
Internal Distractions - Exam 3	-4.351	0.411	
External Distractions - Exam 3	1.365	0.828	
Agreeableness - Exam 3	-0.248	0.869	
Conscientiousness - Exam 3	0.105	0.945	
Model: Predictors of GPA			
$N = 33$, Model $R^2 = 0.110$, Adjusted $R^2 = -0.139$			
Openness - GPA	7.979	0.215	0.110
Neuroticism - GPA	7.494	0.368	
Extraversion - GPA	5.045	0.435	
External Distractions - GPA	9.340	0.736	
Internal Distractions - GPA	-5.282	0.820	
Conscientiousness - GPA	-0.930	0.890	
Agreeableness - GPA	0.417	0.950	
Model: Predictors of Overall Correctness			
$N = 33$, Model $R^2 = 0.332$, Adjusted $R^2 = 0.144$			
Agreeableness - Overall Correctness	0.096	0.039*	0.332

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Table 25 continued

Predictor - Outcome	β	p**-value**	R^2
Extraversion - Overall Correctness	-0.079	0.076	
Internal Distractions - Overall Correctness	0.247	0.119	
Neuroticism - Overall Correctness	0.032	0.563	
Openness - Overall Correctness	-0.017	0.691	
Conscientiousness - Overall Correctness	-0.007	0.875	
External Distractions - Overall Correctness	0.003	0.989	
Model: Predictors of Pause Duration			
$N = 33$, Model $R^2 = 0.315$, Adjusted $R^2 = 0.124$			
Openness - Pause Duration	0.516	0.032*	0.315
Agreeableness - Pause Duration	-0.515	0.040*	
Extraversion - Pause Duration	0.368	0.123	
External Distractions - Pause Duration	0.801	0.427	
Neuroticism - Pause Duration	-0.144	0.631	
Conscientiousness - Pause Duration	0.106	0.666	
Internal Distractions - Pause Duration	0.010	0.990	
Model: Predictors of Submission Frequency			
$N = 33$, Model $R^2 = 0.137$, Adjusted $R^2 = -0.104$			
Agreeableness - Submission Frequency	-14.364	0.207	0.137
Internal Distractions - Submission Frequency	-41.568	0.292	
Openness - Submission Frequency	-10.060	0.350	
Extraversion - Submission Frequency	3.337	0.758	
Neuroticism - Submission Frequency	-3.829	0.783	
External Distractions - Submission Frequency	-8.539	0.855	
Conscientiousness - Submission Frequency	-1.765	0.877	
Model: Predictors of Success Rates			
$N = 33$, Model $R^2 = 0.406$, Adjusted $R^2 = 0.239$			
Agreeableness - Success Rates	0.134	0.015*	0.406
Extraversion - Success Rates	-0.097	0.061	
Internal Distractions - Success Rates	0.331	0.075	
External Distractions - Success Rates	0.087	0.685	
Neuroticism - Success Rates	0.015	0.818	
Conscientiousness - Success Rates	-0.011	0.828	
Openness - Success Rates	0.001	0.992	
Model: Predictors of Successful Submissions			
$N = 33$, Model $R^2 = 0.183$, Adjusted $R^2 = -0.045$			
Openness - Successful Submissions	-3.060	0.114	0.183

Continued on next page

Table 25 continued

Predictor - Outcome	β	p-**value**	R^2
Conscientiousness - Successful Submissions	2.722	0.183	
Agreeableness - Successful Submissions	-2.400	0.232	
Extraversion - Successful Submissions	1.112	0.562	
Internal Distractions - Successful Submissions	-1.996	0.773	
Neuroticism - Successful Submissions	0.399	0.871	
External Distractions - Successful Submissions	0.482	0.953	
Model: Predictors of Total Deletions			
$N = 33$, Model $R^2 = 0.178$, Adjusted $R^2 = -0.052$			
Internal Distractions - Total Deletions	-904.795	0.162	0.178
Openness - Total Deletions	-211.905	0.228	
Conscientiousness - Total Deletions	-164.809	0.375	
Agreeableness - Total Deletions	-139.000	0.447	
Extraversion - Total Deletions	75.318	0.669	
External Distractions - Total Deletions	283.281	0.709	
Neuroticism - Total Deletions	-54.833	0.808	
Model: Predictors of Total Duration			
$N = 33$, Model $R^2 = 0.119$, Adjusted $R^2 = -0.128$			
Neuroticism - Total Duration	55.311	0.477	0.119
Internal Distractions - Total Duration	124.771	0.567	
External Distractions - Total Duration	134.780	0.605	
Conscientiousness - Total Duration	-13.967	0.825	
Openness - Total Duration	-10.772	0.856	
Extraversion - Total Duration	-10.390	0.863	
Agreeableness - Total Duration	-4.976	0.936	
Model: Predictors of Total Events			
$N = 33$, Model $R^2 = 0.169$, Adjusted $R^2 = -0.064$			
Openness - Total Events	-1205.036	0.250	0.169
Conscientiousness - Total Events	-1171.542	0.293	
Internal Distractions - Total Events	-2981.036	0.434	
Neuroticism - Total Events	614.139	0.649	
Agreeableness - Total Events	-456.891	0.674	
Extraversion - Total Events	283.065	0.787	
External Distractions - Total Events	1216.272	0.788	
Model: Predictors of Total Runs			
$N = 33$, Model $R^2 = 0.266$, Adjusted $R^2 = 0.061$			
Conscientiousness - Total Runs	-30.839	0.008*	0.266

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Table 25 continued

Predictor - Outcome	β	p-**value**	R^2
Openness - Total Runs	17.081	0.102	
Internal Distractions - Total Runs	-30.199	0.420	
Neuroticism - Total Runs	2.535	0.848	
Extraversion - Total Runs	-1.918	0.853	
External Distractions - Total Runs	6.330	0.887	
Agreeableness - Total Runs	1.020	0.924	
Model: Predictors of Typing Activity			
$N = 33$, Model $R^2 = 0.112$, Adjusted $R^2 = -0.136$			
Openness - Typing Activity	-511.467	0.274	0.112
Internal Distractions - Typing Activity	-1289.776	0.448	
Conscientiousness - Typing Activity	-236.299	0.632	
Neuroticism - Typing Activity	270.938	0.653	
Extraversion - Typing Activity	117.003	0.803	
Agreeableness - Typing Activity	-117.311	0.809	
External Distractions - Typing Activity	-256.033	0.899	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Conscientiousness - nan	-38.765	0.262	0.188
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Conscientiousness - nan	-37.600	0.275	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Openness - nan	-34.975	0.280	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Openness - nan	-32.973	0.308	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Neuroticism - nan	22.419	0.592	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Neuroticism - nan	20.878	0.617	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
External Distractions - nan	62.182	0.658	

Continued on next page

Table 25 continued

Predictor - Outcome	β	p-value	R^2
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
External Distractions - nan	60.541	0.666	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Extraversion - nan	8.633	0.790	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Agreeableness - nan	-6.586	0.844	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Agreeableness - nan	-6.193	0.854	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Extraversion - nan	5.767	0.859	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Internal Distractions - nan	-9.046	0.938	
Model: Predictors of nan			
$N = 33$, Model $R^2 = 0.188$, Adjusted $R^2 = -0.040$			
Internal Distractions - nan	-4.319	0.971	

*Significant at $p < 0.05$

Table 26 – Multiple Regression Moderation Results - Interaction Terms

Interaction Term	Interaction β	p-value	Raw Sig.
Model Outcome: Avg Duration Per Exercise			
$N = 33$, Model $R^2 = 0.275$, Adj. $R^2 = 0.200$, Model F-test $p = 0.024$			
External Distractions × Neuroticism	37.466	0.052	
Internal Distractions × Extraversion	-14.872	0.143	
Internal Distractions × Agreeableness	-15.415	0.174	
Internal Distractions × Neuroticism	19.823	0.221	
External Distractions × Extraversion	-15.078	0.285	
External Distractions × Agreeableness	-12.567	0.444	
Internal Distractions × Openness	8.445	0.458	
External Distractions × Openness	9.423	0.614	

Continued on next page

Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
Internal Distractions × Conscientiousness	7.110	0.619	
External Distractions × Conscientiousness	-3.706	0.801	
Model Outcome: Avg Events Per Exercise			
$N = 33$, Model $R^2 = 0.172$, Adj. $R^2 = 0.087$, Model F-test $p = 0.134$			
Internal Distractions × Neuroticism	433.598	0.101	
Internal Distractions × Agreeableness	-269.992	0.148	
Internal Distractions × Openness	187.079	0.274	
External Distractions × Neuroticism	306.933	0.344	
External Distractions × Conscientiousness	-186.124	0.386	
External Distractions × Agreeableness	-162.779	0.550	
External Distractions × Openness	-105.355	0.708	
Internal Distractions × Extraversion	-24.968	0.883	
Internal Distractions × Conscientiousness	-11.382	0.957	
External Distractions × Extraversion	8.279	0.971	
Model Outcome: Coding Activity Intensity			
$N = 33$, Model $R^2 = 0.227$, Adj. $R^2 = 0.147$, Model F-test $p = 0.055$			
Internal Distractions × Agreeableness	384.317	0.112	
Internal Distractions × Extraversion	230.295	0.320	
External Distractions × Agreeableness	337.703	0.349	
Internal Distractions × Conscientiousness	132.357	0.691	
Internal Distractions × Neuroticism	-73.570	0.850	
Internal Distractions × Openness	-48.814	0.854	
External Distractions × Neuroticism	-64.283	0.892	
External Distractions × Openness	-44.879	0.918	
External Distractions × Extraversion	-22.361	0.945	
External Distractions × Conscientiousness	4.847	0.989	
Model Outcome: Exam 1			
$N = 33$, Model $R^2 = 0.332$, Adj. $R^2 = 0.263$, Model F-test $p = 0.008$			
Internal Distractions × Openness	-9.566	0.044	*
Internal Distractions × Neuroticism	-8.367	0.289	
External Distractions × Neuroticism	7.956	0.409	
External Distractions × Conscientiousness	5.501	0.434	
External Distractions × Extraversion	-4.985	0.476	
Internal Distractions × Agreeableness	3.105	0.566	
Internal Distractions × Conscientiousness	-3.336	0.623	
External Distractions × Agreeableness	-3.745	0.634	

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
Internal Distractions × Extraversion	1.492	0.768	
External Distractions × Openness	-2.308	0.775	
Model Outcome: Exam 2			
$N = 33$, Model $R^2 = 0.099$, Adj. $R^2 = 0.006$, Model F-test $p = 0.378$			
Internal Distractions × Openness	-8.581	0.097	
Internal Distractions × Conscientiousness	-9.774	0.131	
Internal Distractions × Neuroticism	-9.617	0.208	
External Distractions × Openness	-9.359	0.279	
Internal Distractions × Agreeableness	5.367	0.310	
External Distractions × Extraversion	-4.619	0.485	
External Distractions × Agreeableness	-2.554	0.741	
External Distractions × Conscientiousness	-2.242	0.745	
Internal Distractions × Extraversion	0.988	0.836	
External Distractions × Neuroticism	-0.191	0.984	
Model Outcome: Exam 3			
$N = 33$, Model $R^2 = 0.153$, Adj. $R^2 = 0.065$, Model F-test $p = 0.180$			
External Distractions × Conscientiousness	12.419	0.073	
External Distractions × Extraversion	-9.959	0.140	
Internal Distractions × Neuroticism	-9.210	0.218	
Internal Distractions × Conscientiousness	-6.753	0.307	
Internal Distractions × Openness	-4.820	0.354	
External Distractions × Agreeableness	-7.226	0.366	
Internal Distractions × Agreeableness	2.766	0.605	
External Distractions × Neuroticism	2.599	0.782	
External Distractions × Openness	-2.398	0.787	
Internal Distractions × Extraversion	0.701	0.884	
Model Outcome: GPA			
$N = 33$, Model $R^2 = 0.189$, Adj. $R^2 = 0.105$, Model F-test $p = 0.104$			
Internal Distractions × Openness	-42.050	0.045	*
External Distractions × Extraversion	-43.453	0.114	
Internal Distractions × Conscientiousness	-40.218	0.141	
Internal Distractions × Neuroticism	-40.777	0.202	
External Distractions × Agreeableness	-32.018	0.325	
External Distractions × Conscientiousness	26.384	0.362	
External Distractions × Openness	-32.141	0.368	
External Distractions × Neuroticism	28.964	0.461	

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Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
Internal Distractions × Agreeableness	13.563	0.545	
Internal Distractions × Extraversion	5.536	0.784	
Model Outcome: Overall Correctness			
$N = 33$, Model $R^2 = 0.177$, Adj. $R^2 = 0.091$, Model F-test $p = 0.126$			
External Distractions × Extraversion	-0.190	0.339	
Internal Distractions × Agreeableness	0.150	0.341	
Internal Distractions × Neuroticism	-0.194	0.408	
External Distractions × Conscientiousness	-0.159	0.450	
Internal Distractions × Conscientiousness	-0.102	0.615	
External Distractions × Openness	0.134	0.618	
Internal Distractions × Extraversion	-0.066	0.640	
External Distractions × Neuroticism	0.134	0.642	
External Distractions × Agreeableness	0.061	0.794	
Internal Distractions × Openness	0.016	0.920	
Model Outcome: Success Rates			
$N = 33$, Model $R^2 = 0.267$, Adj. $R^2 = 0.192$, Model F-test $p = 0.027$			
Internal Distractions × Agreeableness	0.174	0.348	
External Distractions × Extraversion	-0.194	0.422	
External Distractions × Conscientiousness	-0.178	0.483	
Internal Distractions × Extraversion	-0.118	0.490	
External Distractions × Neuroticism	0.207	0.549	
Internal Distractions × Neuroticism	-0.162	0.570	
Internal Distractions × Conscientiousness	-0.089	0.716	
External Distractions × Openness	0.115	0.721	
External Distractions × Agreeableness	-0.080	0.772	
Internal Distractions × Openness	0.035	0.856	
Model Outcome: Successful Submissions			
$N = 33$, Model $R^2 = 0.058$, Adj. $R^2 = -0.040$, Model F-test $p = 0.625$			
Internal Distractions × Neuroticism	-11.463	0.254	
Internal Distractions × Extraversion	5.471	0.385	
Internal Distractions × Openness	-5.438	0.420	
External Distractions × Conscientiousness	7.082	0.429	
External Distractions × Neuroticism	8.583	0.483	
Internal Distractions × Agreeableness	3.246	0.634	
External Distractions × Agreeableness	-3.052	0.758	
Internal Distractions × Conscientiousness	-1.655	0.848	

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
External Distractions × Openness	1.829	0.871	
External Distractions × Extraversion	0.526	0.952	
Model Outcome: Total Blur Time			
$N = 33$, Model $R^2 = 0.081$, Adj. $R^2 = -0.014$, Model F-test $p = 0.476$			
External Distractions × Neuroticism	243.622	0.233	
Internal Distractions × Neuroticism	164.623	0.329	
Internal Distractions × Agreeableness	-80.240	0.494	
External Distractions × Extraversion	67.948	0.643	
External Distractions × Openness	-67.806	0.710	
External Distractions × Conscientiousness	-36.743	0.799	
Internal Distractions × Extraversion	22.393	0.833	
External Distractions × Agreeableness	-12.466	0.942	
Internal Distractions × Openness	6.157	0.956	
Internal Distractions × Conscientiousness	0.762	0.996	
Model Outcome: Total Deletions			
$N = 33$, Model $R^2 = 0.069$, Adj. $R^2 = -0.027$, Model F-test $p = 0.551$			
Internal Distractions × Agreeableness	-704.101	0.263	
Internal Distractions × Conscientiousness	692.205	0.359	
Internal Distractions × Neuroticism	767.910	0.405	
External Distractions × Extraversion	-538.650	0.498	
External Distractions × Neuroticism	547.576	0.628	
External Distractions × Agreeableness	-405.428	0.663	
External Distractions × Conscientiousness	278.029	0.731	
Internal Distractions × Openness	152.917	0.798	
Internal Distractions × Extraversion	-128.308	0.823	
External Distractions × Openness	205.787	0.838	
Model Outcome: Total Duration			
$N = 33$, Model $R^2 = 0.213$, Adj. $R^2 = 0.132$, Model F-test $p = 0.070$			
External Distractions × Neuroticism	699.458	0.043	*
External Distractions × Extraversion	-365.748	0.145	
Internal Distractions × Agreeableness	-248.077	0.223	
Internal Distractions × Extraversion	-203.355	0.266	
External Distractions × Agreeableness	-281.010	0.340	
Internal Distractions × Neuroticism	262.109	0.370	
Internal Distractions × Conscientiousness	48.346	0.851	
Internal Distractions × Openness	-15.405	0.940	

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
External Distractions × Conscientiousness	-16.361	0.951	
External Distractions × Openness	-0.250	0.999	
Model Outcome: Total Events			
$N = 33$, Model $R^2 = 0.048$, Adj. $R^2 = -0.050$, Model F-test $p = 0.692$			
External Distractions × Neuroticism	6649.207	0.316	
Internal Distractions × Agreeableness	-3070.635	0.418	
External Distractions × Extraversion	-3667.225	0.438	
External Distractions × Openness	-3263.522	0.582	
External Distractions × Agreeableness	-3013.403	0.585	
Internal Distractions × Openness	-1702.817	0.634	
Internal Distractions × Neuroticism	2047.679	0.711	
External Distractions × Conscientiousness	903.104	0.849	
Internal Distractions × Extraversion	217.697	0.950	
Internal Distractions × Conscientiousness	-213.361	0.962	
Model Outcome: Total Focus Time			
$N = 33$, Model $R^2 = 0.077$, Adj. $R^2 = -0.019$, Model F-test $p = 0.502$			
External Distractions × Neuroticism	236.752	0.248	
Internal Distractions × Neuroticism	158.485	0.349	
Internal Distractions × Agreeableness	-87.934	0.454	
External Distractions × Openness	-97.740	0.593	
External Distractions × Extraversion	55.044	0.708	
External Distractions × Conscientiousness	-36.645	0.799	
External Distractions × Agreeableness	-29.809	0.862	
Internal Distractions × Openness	-13.036	0.907	
Internal Distractions × Extraversion	12.363	0.908	
Internal Distractions × Conscientiousness	-2.347	0.987	
Model Outcome: Total Runs			
$N = 33$, Model $R^2 = 0.200$, Adj. $R^2 = 0.117$, Model F-test $p = 0.087$			
External Distractions × Conscientiousness	66.913	0.156	
Internal Distractions × Neuroticism	75.897	0.184	
Internal Distractions × Openness	34.393	0.379	
Internal Distractions × Agreeableness	-27.492	0.489	
External Distractions × Openness	-41.748	0.520	
External Distractions × Extraversion	-28.243	0.570	
External Distractions × Neuroticism	37.513	0.593	
Internal Distractions × Extraversion	16.121	0.654	

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
External Distractions × Agreeableness	-11.757	0.839	
Internal Distractions × Conscientiousness	-6.122	0.892	
Model Outcome: Typing Activity			
$N = 33$, Model $R^2 = 0.083$, Adj. $R^2 = -0.012$, Model F-test $p = 0.464$			
External Distractions × Extraversion	-3026.296	0.133	
Internal Distractions × Agreeableness	-1745.054	0.283	
External Distractions × Neuroticism	2957.805	0.300	
External Distractions × Agreeableness	-2057.129	0.386	
Internal Distractions × Extraversion	-1071.090	0.467	
Internal Distractions × Openness	-541.725	0.729	
External Distractions × Openness	-866.993	0.740	
External Distractions × Conscientiousness	557.148	0.791	
Internal Distractions × Neuroticism	303.204	0.899	
Internal Distractions × Conscientiousness	97.019	0.961	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Agreeableness	-1.700	0.053	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Extraversion	-1.150	0.163	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Conscientiousness	1.338	0.233	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Conscientiousness	58.032	0.235	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Openness	56.772	0.354	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Conscientiousness	39.128	0.405	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Extraversion	35.143	0.460	
Model Outcome: nan			

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Table 26 continued

Interaction Term	Interaction β	p-value	Raw Sig.
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Extraversion	20.406	0.553	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Agreeableness	-0.743	0.572	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Neuroticism	-0.859	0.599	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Openness	15.063	0.684	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Openness	-0.555	0.693	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Openness	-0.302	0.722	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Extraversion	-0.354	0.760	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Conscientiousness	0.338	0.775	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Agreeableness	7.913	0.832	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Neuroticism	-9.146	0.869	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Agreeableness	6.668	0.903	
Model Outcome: nan			
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
External Distractions × Neuroticism	-7.898	0.907	
Model Outcome: nan			

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Table 26 continued

Interaction Term	**Interaction β**	**p-value**	**Raw Sig.**
$N = 33$, Model $R^2 = 0.176$, Adj. $R^2 = 0.091$, Model F-test $p = 0.127$			
Internal Distractions × Neuroticism	0.092	0.946	

Sig. = Significance ($p < 0.05$)

APPENDIX D

Questionnaires

Table 27 – Distraction Questions

ID	Question
1	I get distracted frequently in practical programming classes.
2	The following interpersonal and intrapersonal aspects cause me distraction: *Socio-affective aspects* *Excessive physical and/or mental fatigue* *Personal worries* *Lack of self-confidence* *Emotional problems*
3	Using my cell phone distracts me during classes or programming sessions.
4	Notifications that appear on my cell phone screen frequently distract me during programming sessions.
5	The following cell phone applications distract me while I am programming: *Instagram* *Facebook* *WhatsApp* *Twitter / X* *TikTok* *YouTube* *Spotify*
6	The following activities distract me during programming sessions: *Reading news*

Table 27 – continued

ID	Question
	Checking personal e-mails *Talking to someone* *Having to stop to sign the attendance sheet*
7	Disinterest in the presented content distracts me.
8	The way or format in which the content is taught is directly related to my distraction towards it.
9	I get more distracted when the programming exercise is challenging.
10	The following environmental aspects cause distraction during programming classes: *Noise* *Lighting* *Temperature* *Room organization* *Ventilation*
11	The following are sources of visual distraction on the computer screen while I program: *Message or e-mail notifications* *Browser tabs open with content unrelated to the class* *Overly complex visual elements in the programming environment* *Pop-ups from programs or sites* *Social media*

Table 28 – Mini-IPIP Questions (Personality)

ID	Question
1	I am the life of the party.
2	I sympathize with others' feelings.
3	I get chores done right away.
4	I have frequent mood swings.
5	I have a vivid imagination.
6	I don't talk a lot.
7	I am not interested in other people's problems.
8	I often forget to put things back in their proper place.
9	I am relaxed most of the time.

Table 28 – continued

ID	**Question**
10	I am not interested in abstract ideas.
11	I talk to a lot of different people at parties.
12	I feel others' emotions.
13	I like order.
14	I get irritated easily.
15	I have difficulty understanding abstract ideas.
16	I keep in the background.
17	I am not really interested in others.
18	I make a mess of my things.
19	I rarely feel sad.
20	I do not have a good imagination.