Individual difference characteristics and contextual factors affecting educational attainment

Maxine Profitt

A Thesis

In the Department of

Psychology

Presented in Partial Fulfillment of the Requirements

For the Degree of

Doctor of Philosophy (Psychology)

at Concordia University

Montréal, Québec, Canada

June 2025

CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: Maxine Profitt

Entitled: Individual difference characteristics and contextual factors affecting educational attainment

and submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY (Psychology)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

______________________________________Chair
Dr. Adam Radomsky

______________________________________External Examiner
Dr. Jessica Whitley

______________________________________External to Program
Dr. Miranda D'Amico

______________________________________Examiner
Dr. Wayne Brake

______________________________________Examiner
Dr. Virginia Penhune

______________________________________Examiner
Dr. Natalie Phillips

______________________________________Thesis Supervisor
Dr. Benjamin Eppinger

Approved by ______________________________________
Dr. Andrew Chapman, Graduate Program Director

September 4, 2025 ______________________________________
Dr. Pascale Sicotte, Dean
Faculty of Arts and Science

Abstract

Individual difference characteristics and contextual factors affecting educational attainment

Maxine Profitt, Ph.D.

Concordia University, 2025

The studies in this dissertation examine cognitive and non-cognitive predictors of postsecondary educational attainment. While prior research has documented links between core cognitive abilities (e.g., processing speed, attention, fluid intelligence) and academic success, less is known about the mechanisms translating these abilities into outcomes. It also remains unclear how contextual disruptions, such as the COVID-19 pandemic impacted students' psychosocial and academic functioning.

The first study investigated the role of learning strategies, along with willingness to engage in effortful cognitive activity (Need for Cognition; NFC), as potential intermediaries between basic cognitive abilities and academic outcomes. Results showed that while standard cognitive measures did not directly predict academic performance, both NFC and model-based (goal-directed) learning strategies were significant positive predictors. Further analyses indicated that fluid intelligence and attention positively predicted NFC and model-based learning, suggesting that these abilities may facilitate the development of motivational and strategic traits that, in turn, promote academic success. These findings emphasize the importance of motivation and strategy use, even when direct associations with basic cognitive abilities are lacking.

The second study complements the first by examining the broader socio-environmental challenges posed by the COVID-19 pandemic on Canadian university students, with a focus on understanding the impact of the pandemic on students' mental health, social networks, SES, and educational attainment. Using longitudinal data collected before and during the pandemic, results revealed that while GPA slightly improved, psychosocial well-being deteriorated. Increases in substance use, smaller social networks, and reduced well-being were observed. Cross-sectional analyses further showed that greater substance use during the pandemic predicted poorer GPA, and students with pre-existing psychiatric conditions were particularly vulnerable to increased

substance use. These findings suggest that students with mental health vulnerabilities may be disproportionately affected by crises, underscoring the need to address maladaptive coping to support academic success.

Together, these studies highlight both individual (e.g., cognition, motivation, learning strategies) and contextual influences (e.g., pandemic disruptions) as important predictors of academic attainment. By considering internal and external factors, this dissertation provides a more comprehensive understanding of the multifaceted determinants of educational success, informing both theory and practice for optimizing university student outcomes.

Dedication

I dedicate this dissertation to my loving grandfather, Gevriye Kucukkaya-Shahho, I will miss you always and forever. Aloho Mhasaloh Baba Rabo, 02-01-2025.

Acknowledgments

I would like to express my sincere gratitude to the members of the Lifespan Decision Making (LDM) Lab for their meaningful contributions to this dissertation and to my research journey more broadly. I am especially thankful to my supervisor, Dr. Benjamin Eppinger, for his dedicated mentorship, thoughtful feedback, and steadfast support throughout every stage of this process. His guidance has been central to my academic and professional growth. Also thank you to Dr. Natalie Phillips who was an immense source of support and encouragement during this process.

Thank you to Dr. Sean Devine, Cassandra Neuman, and Nathalie Germain for their essential help with task development and programming, as well as data collection and organization, which played a critical role in the success of these projects. I am also grateful to Dr. Florian Bolenz for his valuable assistance with task programming and data analyses, and to the rest of the LDM lab for your support, Dr. Alexa Ruel and Jodi Shuat.

Additionally, I extend heartfelt thanks to my friends and peers in the program who provided emotional and psychological support throughout this journey. My writing buddies and best friends, Dr. Mandy Lecocq, Jude Nachabe. I could never have gotten through this program without you. I am also deeply appreciative of my wonderful friends and family who reminded me to take breaks, laugh, and stay grounded. Your presence made all the difference. Mom, Dad, Drs. Josh and Luke, thank you for being my supporters, unconditionally since the beginning of time. My Aunts, Aunt Zumie, Aunt Figen and Aunt Filiz, you are my angels and inspiration on this planet. Nuri, my sweet, beautiful cousin and best friend since we were babies, and Shannon Hall, my dearest best friend from Nova Scotia- you both have been constants in my life, and I am endlessly grateful for your love and support. Finally, my internship supervisors and mentors at Tewksbury Hospital, Dr. Tripti Bhaskar, Dr. Brendan Lynch and David Cook, your support this past year post internship has been critical to my success and completion during the last stretch of this degree. Thank you all.

Contribution of Authors

This dissertation consists of two manuscripts. For both papers, in collaboration with my supervisor, I designed the research questions and studies, performed data collection, statistical analyses and wrote the manuscripts. Additional contributions of my co-authors to each study are detailed below.

Study 1:

Profitt, M., Devine, S., Bolenz, F., & Eppinger, B. (2025, June 11). Willingness or ability? Motivational and cognitive underpinnings of educational attainment in younger adults. https://doi.org/10.35542/osf.io/zj2cv_v1

Sean Devine contributed by programming the experimental tasks and helping to set up the study's core paradigms. Florian Bolenz programmed the computational modeling task and performed the associated analyses. Benjamin Eppinger provided support with data analysis and conceptual framing. All three co-authors contributed to editing the manuscript and offering feedback throughout the writing process.

Study 2:

Profitt, M., Germain, N., Ast, E. M., & Eppinger, B. (2025, June 14). Impact of the COVID-19 Pandemic on mental-health and academic performance in Canadian university students. https://doi.org/10.35542/osf.io/x5tj4_v1

Nathalie Germain assisted in the design of the study, programmed the online questionnaire, and managed participant recruitment, data collection and collation. Ena Michelle Ast supported the project by assisting with data collation and providing written feedback on the manuscript. Benjamin Eppinger contributed to the study design, assisted with data analysis, and provided writing feedback, guidance and edits.

Table of Contents

List of Figures

List of Tables

CHAPTER ONE:

GENERAL INTRODUCTION

UNDERSTANDING THE FACTORS THAT DRIVE EDUCATIONAL ATTAINMENT, DISSERTATION OBJECTIVES, AND OVERVIEW

The Importance of Higher Education and Academic Success

Higher education plays a critical role in shaping both individual and societal outcomes (Baum et al., 2013). Earning a college degree is associated with numerous benefits, including greater financial stability, increased job security, and enhanced overall well-being (Baum et al., 2013; Carnevale et al., 2016; U.S. Bureau of Labor Statistics, 2024). Given these advantages, understanding the factors that contribute to academic success has been a key focus of research. Multiple disciplines, including psychology, educational science and social sciences, have tried to identify individual predictors of educational attainment (DeBerard et al., 2004; Dubuc et al., 2022; Duckworth et al., 2019; Geary, 2011). Most of this work has relied on self-report measures and standardized psychological assessments. Findings consistently show that cognitive abilities such as fluid intelligence, processing speed, working memory, attention and executive functions (Malykh et al., 2017; Tikhomirova et al., 2020; Zaboski et al., 2018; Zisman & Ganzach, 2022), along with motivational and personality characteristics, are important predictors of academic success (Cetin, 2015; Cetin, 2021; Cole, 1974; Komarraju et al., 2009; Laidra et al., 2007; Meier et al., 2014; Morosanova et al., 2022; Zimmerman, 2011). However, the psychological mechanisms that underlie these associations remain poorly defined, and the boundary conditions and educational contexts in which these relationships emerge are still understudied. In addition to individual differences in cognitive and motivational traits, external stressors also play a critical role in shaping academic outcomes and must be considered to gain a more comprehensive understanding of the correlates of educational attainment (Cao et al., 2024; Fahle et al., 2023; Hu et al., 2022; Izumi et al., 2021; Reyes-Portillo et al., 2022). In this dissertation I use assessments of cognitive, motivational and personality characteristics, ranging from “molecular” measures of individual differences in computational learning processes, to self-report scales and objective testing batteries to predict educational outcomes in university students. Additionally, I study how fundamental changes in the boundary conditions of learning during the COVID-19 pandemic affect educational success.

How is College Student Performance Measured?

Prior to examining the various influences on student outcomes, it is essential to first clarify how academic success itself is typically defined and measured in postsecondary research. In postsecondary education, student performance is most commonly represented by grade point average (GPA), which reflects the mean of weighted course marks contributing to degree attainment (Richardson et al., 2012). GPA is considered the primary criterion for postgraduate opportunities and has been shown to predict later occupational success (Richardson et al., 2012; Strenze, 2007). It is widely recognized as an objective measure with good internal reliability and temporal stability (Bacon & Bean, 2006; Kobrin et al., 2008), though questions of validity have been raised due to grade inflation (Johnson, 2003) and institutional grading differences (Didier et al., 2006). Despite these limitations, GPA remains the most widely used indicator of university academic performance, surpassing behavioral markers including hours spent studying, which show negligible correlations with GPA (Plant et al., 2005). Moreover, evidence from college admissions research indicates that high school grades consistently predict college GPA more strongly than standardized test scores such as the SAT, thereby reinforcing the validity of GPA as a measure of academic performance (Geiser & Santelices, 2007). Beyond cumulative GPA, researchers sometimes incorporate additional indicators of student achievement such as term or course grades, credit totals, student retention and graduation completion rates. Such measures can capture both short-term performance and long-term persistence. In addition, standardized assessments (e.g., the Collegiate Learning Assessment) are used to assess higher-order skills such as critical thinking, problem solving, and written communication. These measures are designed to assess aspects of learning that may not be fully captured by GPA or grades alone, thus providing a broader perspective on student learning and development in higher education (Arum & Roksa, 2011). Overall, although GPA remains the dominant benchmark and indicator of university academic performance- serving as the main outcome measure in the present dissertation- recognizing the value of complementary indicators emphasizes the multifaceted nature of academic success and the complexities involved in examining its predictors.

Research Scope and Dissertation Objectives

This dissertation is structured around two complementary studies. Specifically, the first study examines the role of cognitive abilities, motivation, and goal-directed learning strategies in predicting academic performance in university students. The second study extends this investigation by leveraging a unique opportunity presented by the COVID-19 pandemic, allowing for both a longitudinal and cross-sectional examination of how students adapted to this large-scale disruption. The following section outlines the study design, detailing the data collection process, key variables, and methodological approach for both time points.

Context and Rationale of the Studies

Data collection for the first study, considered Timepoint 1 (T1), took place between March 2019 and March 2020. During this period, I gathered extensive data on participants, including cognitive test scores, demographic information, socioeconomic status (SES), social networks, medical and mental health, substance use, and academic outcomes. As part of the study protocol, participants first completed an online pre-laboratory questionnaire, followed by the administration of computer-based cognitive tasks and standardized assessments conducted in the laboratory. Unexpectedly, in March 2020, the COVID-19 pandemic emerged, causing widespread disruptions across multiple sectors, including education (Cullen et al., 2020; Hu et al., 2022; Li et al., 2020; Lowe et al., 2023a; Yang et al., 2020). Schools worldwide initially closed for several weeks in an effort to contain the virus, followed by a transition to online learning for several months, and later, a hybrid model combining in-person and remote instruction (Conroy et al., 2020; Hu et al, 2022; Wang et al., 2020). This presented an opportunity to examine the pandemic's impact on students' psychosocial functioning and educational attainment. To investigate these effects, I conducted a follow-up study one year into the pandemic (Timepoint 2; T2), with data collection spanning from March 2021 to April 2021. This reassessment aimed to track changes in academic attainment, mental health outcomes, social networks, substance use, and SES, while also incorporating new variables relevant to the pandemic context. Academic performance at T2 reflected students' cumulative grade point average as of the end of the Fall 2020 semester (December 2020), which encompasses all coursework completed up to that point- and importantly included Fall 2020- the first major semester affected by the pandemic. This allowed us to examine the immediate impact of pandemic-related disruptions on educational outcomes while assessing other psychosocial factors in March 2021.

Dissertation Structure

The current (first) chapter of this dissertation introduces the topic of educational attainment and the importance of studying predictors of cognitive and non-cognitive predictors as well as external stressors. The second chapter encompasses the first study, addressing, cognitive and motivational aspects related to learning and academic attainment at the post-secondary level. The third chapter contains the second study of this dissertation, which examines the impact of the COVID-pandemic on the mental health and academic performance of university students. Last, the fourth and final chapter discusses the individual contributions and collective insights of both studies, addressing overarching findings, limitations, strengths, future directions and implications of the present research on predictors of educational attainment.

Contributions and Implications

This dissertation advances the literature on educational attainment by adopting a broader, multi-dimensional perspective that considers both individual and contextual factors. By examining the roles of cognitive abilities, motivational dispositions, and external socio-environmental influences, the present work offers a more comprehensive understanding of the mechanisms underlying academic success. Although the two studies were conducted separately, together they illustrate the importance of considering multiple levels of influence when evaluating predictors of educational outcomes. These findings contribute not only to theoretical models of academic achievement but also have practical implications for the design of educational policies and interventions.

COGNITIVE PREDICTORS OF EDUCATIONAL SUCCESS

The link between cognitive abilities and educational attainment

Cognitive abilities have been a prominent focus of research on academic achievement, with studies consistently demonstrating their impact on student performance (Cattell, 1987; Duckworth et al., 2019; Frey & Detterman, 2004; Luo et al., 2003; Malanchini et al., 2019; Peng et al., 2019; Sternberg et al., 2008). Specifically, it has been well-documented that cognitive abilities, including but not limited to fluid intelligence (Cattell, 1987; Malanchini et al., 2019; Sternberg et al., 2008); processing speed (Rodic et al., 2014; Rohde & Thompson, 2007), working memory (Laidra et al., 2007; Tikhomirova et al., 2019) and cognitive control (Deary et al., 2007; Otto et al. 2015) are important predictors of educational attainment. However, they do not fully explain the variability in academic outcomes, suggesting that other factors-such as motivation, emotional well-being, as well as external environmental influences-also play a critical role in predicting academic success (Cao et al., 2024; Ferrer et al., 2023; Izumi et al., 2021; Reyes-Portillo et al., 2022; Shi & Qu, 2021; Shi & Qu, 2022a; Shi & Qu, 2022b). Additionally, higher-order processes such as meta-cognition have been proposed to facilitate the translation of basic cognitive abilities into meaningful academic performance (Shi & Qu, 2022a). Other higher-order cognitive processes, such as usage of goal-directed learning strategies-which rely on cognitive control and prospective planning- has been shown to correlate with cognitive ability (Daw et al., 2011; Eppinger et al., 2013; Otto et al., 2015), however its role in educational attainment remains unexplored. Understanding the scope and the limitations of these contributions is important for developing a more comprehensive model of academic success.

Metacognition and the Use of Learning Strategies

While cognitive abilities are foundational to academic success, the mechanisms by which students manage and regulate their cognitive resources are also critical, as effective self-regulation can optimize learning, sustain motivation, and help students adapt to academic challenges (Abdelrahman, 2020; Coutinho, 2007; Dangin et al., 2023; Fidrayani et al., 2020; Gul & Shehzad, 2012). In cognitive and computational psychology these mechanisms are often referred to as meta-cognitive processes or strategies (Lieder & Griffiths, 2017; Sloman et al., 1996). These are higher-order systems that allow individuals to monitor, control and regulate the engagement of lower-level cognitive functions, such as different learning strategies, inhibitory control and memory retrieval (Bolenz et al., 2022; Eppinger et al., 2013; Eppinger et al., 2021). Reinforcement learning frameworks (Sutton & Barto, 1998) have been used to model meta-level processes during learning and decision-making (Daw et al., 2011; Kool et al., 2017). One leading theory (Daw et al., 2011) posits that decision behavior is learnt via two distinct strategies: a habitual (model-free) learning process, which relies on trial-and-error learning of action-outcome associations, and a more sophisticated, goal-directed (model-based) strategy, which involves forming mental representations of task structures to guide future actions. Model-free learning is computationally cheap but lacks flexibility, as changes in the environment require new behaviors to be learned from experience. In contrast, model-based learning, which demands greater cognitive resources, offers more flexibility in dynamic environments by allowing the individual to learn and apply task structures (Bolenz et al., 2022; Dayan & Niv, 2008; Kool et al., 2017; Otto et al., 2015). Accordingly, individual differences in cognitive resources, including working memory and cognitive control have been shown to predict the extent to which people rely on model-based strategies (Eppinger et al., 2013; Otto et al., 2015). Importantly, however, the use of model-based learning is not inherently a metacognitive process. Rather, metacognition in this context refers to the regulation of when and to what extent model-based strategies are engaged, depending on environmental demands and internal resource constraints. In tasks where reward contingencies vary across conditions, participants must decide whether it is worth investing the cognitive effort required for model-based control, depending on how much reward is at stake. This ability to adapt one's learning strategy in response to reward contingencies (termed meta-control) represents a metacognitive process that governs the allocation of cognitive effort across contexts (Kool et al., 2017).

As such, the current dissertation focuses on both the overall tendency to engage in model-based learning (across high- and low-stakes contexts) and the meta-control of learning strategy (i.e., the modulation of model-based engagement as a function of reward). Given that engagement in model-based strategies place significant demands on cognitive resources, it is unsurprising that prior research has shown that individual differences in cognitive control and working memory predict use of model-based learning engagement (Eppinger et al., 2013; Otto et al., 2015). Otto et al. (2015) investigated the link between cognitive control and model-based learning in a sequential choice task. Their findings revealed that greater Stroop task interference was negatively correlated with model-based decision-making. Accordingly, individuals who exhibited stronger cognitive control (and thus less Stroop interference) were more likely to use the deliberative model-based strategy. Similarly, Eppinger et al. (2013) found that working memory performance was predictive of use of model-based strategies in decision-making.

While these studies suggest that there is an overlap between model-based learning and cognitive abilities, it remains unclear whether and to what degree these sophisticated learning strategies influence academic attainment. Importantly, while several studies have looked at how individual differences in basic cognitive abilities affect educational attainment, the higher-level learning processes that translate these basic abilities (such as WM or cognitive control) into academic outcomes have received far less attention. To address this gap, the present research uses experimental and computational methods to examine how both goal-directed learning and its regulation (i.e., meta-control) contribute to academic performance. By focusing on these dynamic, higher-level learning processes, the dissertation aims to provide a more mechanistic understanding of how students leverage cognitive and motivational resources to succeed in higher education.

NON-COGNITIVE PREDICTORS OF EDUCATIONAL SUCCESS

In addition to cognitive factors, non-cognitive predictors play a vital role in shaping academic outcomes by fostering motivation, promoting engagement, and supporting productive learning habits (Bjorklund-Young et al., 2016; Cao et al., 2024; Duckworth et al., 2019). Such factors may also enhance and support the development of cognitive skills essential for academic achievement, making them a critical component of a comprehensive understanding of academic success (Shi & Qu, 2022a). Specifically, studies have identified several key non-cognitive factors associated with academic achievement. These include academic behaviors such as course attendance and class participation (Farrington et al., 2012), interpersonal skills like communication and collaboration (Farrington et al., 2012), intrapersonal traits such as perseverance, grit, self-discipline, and motivation (Duckworth et al., 2019; Morosanova et al., 2022), as well as broader personality characteristics (Ruffing et al., 2015).

Motivational constructs have been assessed through various methods, including self-report measures such as the *Need for Cognition* (NFC) scale (Cacioppo et al., 1984). Specifically, the NFC reflects an individual's tendency to engage in and enjoy effortful cognitive activities, and has been linked to greater academic engagement, utilization of deeper learning strategies, and ultimately, stronger academic performance (Cacioppo et al., 1996; Neigel et al., 2017). Specifically, a high NFC has been associated with higher GPAs and standardized exam scores, as well as greater performance on intelligence tests (Fleischhaur et al., 2010; Hawthorne et al., 2021; Liu & Nesbit, 2024). Furthermore, a more recent study found that students that score high on NFC exhibit positive attitudes toward problem-solving and a strong engagement in information processing (Colling et al., 2022). Generally speaking, high NFC individuals derive personal satisfaction from engaging in cognitively demanding activities, and are believed to handle mentally stimulating tasks more effectively (Grass et al., 2017; Gray et al., 2015; Meier et al., 2014). Conversely, students with lower NFC report less fulfillment from intellectual engagement and tend to prefer structured learning approaches with greater guidance (Evans et al., 2003).

So far, these findings highlight the importance of both strategic and motivational processes in influencing academic achievement. Building on this literature, this dissertation seeks to examine how individual differences in learning strategies (described in section 2) and motivational constructs such as the NFC, contribute to academic outcomes. In doing so, I take into account not only what students know, but also how they engage with learning and why they choose to invest cognitive effort. By examining both higher-order cognitive mechanisms like model-based learning and motivational processes that promote effortful cognitive engagement, this work aims to provide a more mechanistic and integrative account of the factors that support educational attainment.

IMPACT OF THE COVID-19 PANDEMIC

Although cognitive abilities and motivational traits contribute to academic success (Cao et al., 2024; Duckworth et al., 2019; Liu & Nesbit, 2024; Shi & Qu, 2021; Tikhomirova et al., 2020), educational attainment is also influenced by external disruptions, such as the COVID-19 pandemic (Borgaonkar et al., 2021; Ferrar et al., 2023; Haynes et al., 2024; Mahdy, 2020 Reyes-Portillo et al., 2022). This unprecedented global stressor provided an opportunity to evaluate how such disruptions alter student outcomes and modify established predictors of educational attainment.

Impact of the COVID-19 pandemic on the education system

The COVID-19 pandemic introduced unprecedented challenges that impacted education systems worldwide (Aristovnik et al., 2020; Fahle et al., 2023; Haynes et al., 2024; Kuhfeld et al., 2023; Reyes-Portillo et al., 2022). As schools closed and academic instruction shifted to online platforms, students- particularly those already vulnerable to mental health and financial strains- faced pandemic related challenges that further impacted their academic outcomes (Aucejo et al., 2020; Fahle et al., 2023; Ferrer et al., 2023; Hu et al., 2022; Li et al., 2020). The pandemic affected academic achievement to varying degrees, depending on students' education level, study subject or major, and socioeconomic status (SES) (Borgaonkar et al., 2021; Clark et al., 2021; Fahle et al., 2023; Haynes et al., 2024, Kuhfeld et al., 2022; LaGuardia Community College, Office of Institutional Research and Assessment, 2022; Mahdy, 2020; Vautier et al., 2023). While many studies have demonstrated declines in academic performance as a result of the COVID-19 pandemic (Borgaonkar et al., 2021; Fahle et al., 2023; Haynes et al., 2024; Mahdy, 2020), others have shown improvements in some academic outcome measures (Clark et al., 2021; LaGuardia Community College, Office of Institutional Research and Assessment, 2022).

Among elementary students, grades in math and reading declined by 2021 compared to pre-pandemic levels, with greater declines seen in lower SES students (Fahle et al., 2023; Kuhfeld et al., 2022). Findings among college students are more mixed, with some studies showing declines in academic performance, particularly in hands-on fields like veterinary medicine and engineering, where remote learning hindered practical experiences (Borgaonkar et al., 2021; Mahdy, 2020). Borgaonkar et al., 2021 attributed these academic losses to reduced motivation and class attendance during the transition to online learning. Additionally, approximately one-third of a nationally representative sample of U.S. college students reported receiving lower grades than expected as a result of the pandemic (Haynes et al., 2024), while other research documented delays in graduation and pandemic-related job loss in college students, highlighting the broader impacts on students' academic and professional trajectories (Aucejo et al., 2020). Conversely, some studies noted academic improvements during the pandemic, particularly among lower-achieving students, who obtained better grades during lockdown, while the highest-achieving students showed little to no academic improvement (Clark et al., 2021). Institutional reports also showed mixed outcomes. A report on students from LaGuardia Community College in New York revealed mixed trends in GPA by subject, with English pass rates decreasing while Math pass rates increased (LaGuardia Community College, Office of Institutional Research and Assessment, 2022). Notably, changes in grading regimes or assessment methods during the pandemic may help explain some of these unexpected gains in academic performance (Vautier et al., 2023). Despite these trends, first-year enrollment and retention rates fell, particularly among lower-income and minority students, highlighting ongoing disparities in access and opportunity (LaGuardia Community College, Office of Institutional Research and Assessment, 2022).

Evidently, the pandemic impacted student educational outcomes in different ways (Borgaonkar et al., 2021; Clark et al., 2021; Fahle et al., 2023; Ferrer et al., 2023; Haynes et al., 2024, Hu et al., 2022; Kuhfeld et al., 2022; LaGuardia Community College, Office of Institutional Research and Assessment, 2022; Mahdy, 2020; Vautier et al., 2023), however the specific factors that contributed to pandemic-related changes in academic performance remains to be determined. In the next section, I attempt to understand such variables that led to academic performance changes during the pandemic.

Factors that led to academic performance changes and learning loss during the pandemic

Academic losses related to the pandemic have been hypothesized to be related to a variety of interrelated factors including but not limited to: shifts to remote learning (Fahle et al., 2023), lower SES (Aucejo et al., 2020; Ferrer et al., 2023; Reyes-Portillo et al., 2022), financial strains due to COVID-19, such as lost jobs and wages, difficulty paying for housing and food (Fahle et al., 2023; Haynes et al., 2024). These stressors were compounded by increased mental health challenges, with many students reporting heightened anxiety and depression during the pandemic (Aristovnik et al., 2020; Cao et al., 2020; Hu et al., 2022; Sauer et al., 2022; Son et al., 2020). Notably, in response to these disruptions, students withdrew from school, took leaves of absence, and canceled their courses altogether (Haynes et al., 2024).

Remote learning challenges: More specifically, the abrupt shift to remote learning posed significant challenges (Garris & Fleck, 2020), especially for students lacking access to reliable technology, educational resources or quiet study spaces (Bekerman & Rondanini; 2020; David et al., 2022). In fact, it has been documented that school districts that utilized remote learning for longer in the 2020-2021 period suffered greater academic losses (Fahle et al., 2023). The need for heightened self-discipline in managing coursework from home created additional strain, especially for students with existing mental health issues such as attention deficits at the secondary level (Becker et al., 2020). Additionally, some claim that reduced in-person interaction hindered collaborative learning, further exacerbating academic difficulties for post-secondary students (Bekerman & Rondanini, 2020).

Interestingly, Ferrer et al. (2023) found that students who rated online instruction positively tended to perform better academically, while those with limited access to educational resources and facing mental health challenges performed worse. These findings highlight the importance of examining the factors that influenced students' adaptability to remote learning, which may be important for identifying why some students thrived academically while others struggled.

Socioeconomic (SES) and demographic disparities: Socioeconomic disparities significantly magnified negative effects related to the pandemic, with students from lower SES backgrounds more vulnerable to financial and health impacts of the COVID-19 pandemic (Bhagavathula & Khubchandani, 2023). Students with lower SES experienced higher dropout rates and economic challenges that often delayed graduation, and exacerbated existing educational inequalities (Aucejo et al., 2020). In addition, the literature has also highlighted that students of color faced the most COVID-related, financial and academic difficulties which likely are related to longstanding systemic inequities compared to their non-minority peers (Reyes-Portillo et al., 2022).

While prior studies have linked pandemic-related academic losses to community-level factors such as loss of broadband access or economic disruption, these variables alone do not provide strong explanatory power for the academic changes observed during the pandemic (Faynes et al., 2023). This suggests that a combination of community and individual-level psychosocial factors likely interacted to influence students' academic trajectories.

Mental Health Challenges: In particular, individual-level factors, such as students' mental health and coping behaviors, may have played a role in influencing academic outcomes during this period of disruption. Indeed, as previously stated, the pandemic significantly exacerbated mental health issues on a global scale (Cao et al., 2020; Copeland et al., 2020; Cullen et al., 2020; Fruehwirth et al., 2025; Pfefferbaum et al., 2020; Sauer et al., 2022; Xiong et al., 2020). Data from the U.S. Department of Education's Institute of Education Sciences reported that 73% of college freshmen during the 2019–20 school year experienced pandemic-related stress and anxiety (Haynes et al., 2024), with students facing greater financial instability (i.e., manifesting in higher rates of employment loss and difficulty paying for necessities such as food and shelter) reporting more severe symptoms (Haynes et al., 2024; Reyes-Portillo et al., 2022). University students with pre-existing anxiety and depression experienced greater levels of pandemic-related stress (David et al., 2022; Reyes-Portillo et al., 2022). In parallel, substance use increased significantly during the pandemic in high-school and college students, which was usually associated with poorer mental health outcomes (Charles et al., 2021; Dumas et al., 2020; Pelham et al., 2021). Specifically, increased substance use during the pandemic correlated with depression and anxiety symptoms, although how these trends impacted overall academic performance remains less clear (Dumas et al., 2020). Given the well-documented rise in psychological distress and substance use among students during the pandemic, it is of relevance to investigate how these mental health vulnerabilities may have shaped academic outcomes, an area that remains underexplored, particularly through longitudinal designs using objective academic metrics such as GPA.

Social Isolation: During the COVID-19 pandemic, social distancing measures and the shift to remote learning significantly reduced students' social networks (Aristovnik et al., 2020; Banerjee & Rai, 2020; Jeffers et al., 2022), leading to increased isolation and loneliness (Son et al., 2020; David et al., 2022). This reduction in social connectedness has been strongly linked to elevated levels of anxiety and depression, particularly in university populations (Li et al., 2020). Given the well-established relationship between poor mental health and academic functioning (Maghalian et al., 2023; Son et al., 2020; Unger, 2007), diminished social support during the pandemic may have indirectly contributed to declines in academic performance. As such, isolation represents a potential psychosocial factor in understanding students' vulnerability to academic disruption during this period.

Taken together, these findings suggest that pandemic-related academic performance changes in university students were potentially driven by a combination of factors that include structural barriers, socioeconomic disadvantage, and individual-level psychological vulnerabilities (e.g., pre-existing mental health conditions and maladaptive coping behaviors such as increased substance use). However, most existing research has focused on K–12 populations and many college-level studies have relied on students' subjective perceptions of academic performance. As such, there remains a gap in understanding the mechanisms through which the pandemic influenced university students' academic attainment, particularly through studies employing longitudinal designs and objective measures like GPA.

THESIS STUDY RATIONALES AND MAIN HYPOTHESES

The studies of this dissertation provide an overview of several important cognitive and non-cognitive predictors of educational attainment, aiming to address gaps in our understanding of the factors that contribute to academic performance at the collegiate level. While prior research has explored the relationship between basic cognitive abilities (such as processing speed, attention, and fluid intelligence) and academic success (Best & Miller, 2010; Cattell, 1987; Frey & Detterman, 2004; Malanchini et al., 2019; Peng et al., 2019; Tikhomirova et al., 2020), the question of how these abilities are translated into educational outcomes has received less attention. In addition, motivational traits such as the Need for Cognition (NFC) (which reflects an intrinsic motivation toward mental engagement and learning) has been examined in college populations (Grass et al., 2017; Hawthorne et al., 2021; Neigel et al., 2017), but remain less frequently emphasized relative to more established cognitive predictors of educational attainment. Moreover, higher-order cognitive processes, including goal-directed learning strategies and their meta-control, have been largely unexamined in the literature on academic success.

Finally, few models have integrated both cognitive and motivational predictors to examine their joint and unique contributions to academic success (Cao et al., 2024; Morosanova et al., 2022). In addition, it remains unclear how external disruptions, such as the COVID-19 pandemic, may have influenced academic outcomes by altering individual-level factors such as mental health and well-being, social networks, and socioeconomic status (SES).

In total, this dissertation seeks to advance our understanding of both individual-level and contextual predictors of educational attainment, offering a more comprehensive framework for examining academic success. Below, each study's aims and predictions are summarized.

Chapter 2- Study 1: Addressing the Cognitive-Motivational Interface

Purpose and Objectives:

While previous research has emphasized the role of basic cognitive abilities such as working memory, fluid intelligence, and processing speed in predicting academic success (Best & Miller, 2010; Cattell, 1987; Frey & Detterman, 2004; Malanchini et al., 2019; Peng et al., 2019; Tikhomirova et al., 2020), less is known about the higher-level learning and motivational processes that may contribute to educational attainment above and beyond these foundational cognitive abilities (Baars et al., 2015; Cao et al., 2024; Grass et al., 2017; Shi & Qu, 2021; Shi & Qu 2022a; Shi & Qu 2022b; Morosanova et al., 2022; Zimmerman, 2011). Specifically, characteristics such as individuals' willingness to exert mental effort and their ability to flexibly engage in strategic, goal-directed learning may play an important role in supporting academic performance. The aim of the first study is to examine whether the use of cognitive abilities (including fluid intelligence, attention, and processing speed), model-based learning strategies, and motivational factors (i.e., the Need for Cognition (NFC), which reflects an intrinsic motivation to engage in mentally demanding tasks) predict academic outcomes, as measured by high school grades and university GPA. The study also explores how individuals allocate cognitive effort in response to varying reward contingencies. This study adopts an experimental and computational approach to capture higher-level learning strategies, including participants' general tendency to engage in model-based learning and their ability to adjust strategy use depending on reward contingencies. By evaluating the contributions of both cognitive capacity and motivated learning behavior, the study aims to offer more detailed insights into the individual factors that support academic success in higher education.

Key Predictions:

The following predictions represent the primary hypotheses guiding the first study, though they do not encompass all analyses conducted:

1. Cognitive abilities will positively predict model-based learning engagement.
2. Cognitive abilities will positively predict NFC.
3. NFC and model-based learning strategies will each positively predict educational attainment (grades in high school and college GPA).

Chapter 3- Study 2: Exploring Contextual Influences: The COVID-19 Pandemic

Purpose and Objectives:

The second study examines the impact of the COVID-19 pandemic on Canadian university students' academic performance, mental health and psychosocial outcomes. Using a longitudinal approach that based on data collected from before and during the pandemic, I assessed changes in students' GPA, mental well-being, substance use, social networks, and socioeconomic status (SES). In addition, I acquired a multitude of variables including measures of anxiety and depressive symptoms, daily functional impairment, and pandemic-related stress and anxiety, to understand student responses to the pandemic and factors underlying potential declines in academic performance.

Key Predictions:

1. GPA, social networks, subjective SES and mental well-being will decline, while substance use will increase following onset of the pandemic.

2. Pre-existing mental health conditions will be associated with poorer mental health outcomes at T2 (i.e., during the pandemic).
3. Mental health measures will be linked to poorer academic outcomes at T2 (i.e., during the pandemic).

Summary

Taken together, the two studies aim to enhance our understanding of the cognitive, motivational and contextual factors that contribute to educational attainment and the broader well-being of university students, both pre and post COVID-19 pandemic. By examining cognitive, meta-cognitive and motivational predictors of academic success in the first study, and assessing the pandemic's impact on students' mental health, psychosocial functioning, and academic performance in the second, this dissertation highlights the multifaceted and dynamic nature of educational attainment. These findings offer valuable insights into the mechanisms through which both cognitive influences including strategic learning, motivation, as well as external stressors (e.g., pandemic-related disruptions) impact academic performance. Ultimately, this work emphasizes the importance of adopting an integrative, student-centered approach to educational support, including one that considers cognitive capacity, motivational engagement, and psychosocial well-being and adaptation as interconnected drivers of academic success.

CHAPTER TWO:

STUDY 1

Willingness or ability? Motivational and cognitive underpinnings of educational attainment in younger adults.

Abstract

In this study we examined cognitive and motivational underpinnings of educational attainment in younger adults. In particular, we were interested in whether cognitive abilities and/or the willingness to engage in cognitively effortful behaviour differentially predict educational outcomes. To assess cognitive function, we applied a broad range of well-established measures of cognitive abilities as well as a sequential decision-making task that provides a computational proxy for goal-directed learning and decision strategies. To assess inter-individual differences in the willingness to engage in cognitively effortful behavior we used the need for cognition (NFC) questionnaire and two experimental paradigms that assessed the effects of reward sensitivity on cognitive effort expenditure. The results show that 1) Goal-directed decision strategies and NFC are positively associated with university grade point average (GPA) whereas cognitive abilities show no direct relationship to educational outcomes. 2) Goal-directed learning and decision-strategies are positively predicted by cognitive abilities (fluid intelligence and attention) 3.) NFC is also positively predicted by fluid intelligence, and shows a negative association with reward sensitivity. In short, these findings highlight the importance of looking beyond cognitive ability alone to consider how motivational traits and goal-directed learning strategies contribute to educational success.

Introduction

A variety of factors contribute to academic success, including both cognitive and motivational or emotional influences (Cole, 1971; Cetin, 2015; DeBerard et al., 2004; Zisman & Ganzach, 2022). In particular, the role of cognitive abilities in predicting educational attainment has been studied extensively (Best & Miller, 2010; Cattell, 1987; Frey & Detterman, 2004; Luo et al., 2003; Malanchini et al., 2019; Peng et al., 2019; Sternberg et al., 2008). Unsurprisingly, a wide range of cognitive measures, including processing speed (Luo et al., 2006; Rodic et al., 2015; Rohde & Thompson, 2007), working memory (Laidra et al., 2007; Tikhomirova et al., 2020) and cognitive control (Deary et al., 2007) have been linked to better educational outcomes. Above all, fluid intelligence seems to be one of the strongest and most reliable predictors of achievement in various academic domains, across age, education level, social and economic contexts (Deary et al., 2007; Geary, 2011; Laidra et al., 2007; Tikhomirova et al., 2020; Verbitskaya et al., 2020). Taken together, these findings emphasize the importance of cognitive abilities for academic success. However, much less is known about the psychological and computational mechanisms underlying these abilities and their relationship to achievement.

Learning Strategies and the Metacontrol of Decision-Making

One set of candidate mechanisms that may play a role for both cognitive abilities and educational attainment are reinforcement learning strategies (Sutton & Barto, 1998), particularly habitual, ormodel-free and goal-directed or model-based learning (Daw et al., 2011). These learning strategies differ in their cognitive demands and flexibility. Model-free learning is a low-effort strategy that updates behavior based on trial-by-trial reinforcement. It is computationally inexpensive but relatively inflexible in the face of changing environments. In contrast, model-based learning relies on building and using internal models of task structure to guide behavior. This approach demands more cognitive resources but allows for greater flexibility and adaptability (Dayan & Niv, 2008; Kool et al., 2017; Otto et al., 2015).

A growing body of research has examined how individuals regulate their use of model-based and model-free strategies in response to internal cognitive resources and external demands, a process referred to as metcontrol (Eppinger et al., 2013; Lieder & Griffiths, 2017; Sloman et al., 1996). Metacontrol involves higher-order regulatory processes that arbitrate between competing decision strategies (e.g., whether to use model-free or model-based learning) based on contextual factors such as reward contingencies, task complexity, or effort costs (Kool et al., 2017).

In this framework, model-based and model-free learning represent first-order cognitive mechanisms, while the regulation or arbitration between them reflects meta-level control processes. These meta-level processes, which are grounded in computational models and experimentally testable, are thought to play a critical role in how individuals adapt their behavior to complex and changing environments. The current study leverages this computational framework to investigate how individual differences in learning strategy engagement and metacontrol processes relate to academic performance.

Relationship between model-based decision-making and cognitive abilities

Because the model-based strategy depends strongly on cognitive resources, it is unsurprising that previous work has linked individual differences in cognitive control and working memory to the use of this strategy. For instance, Otto et al. (2015) explored how individual differences in cognitive control predict model-based reinforcement learning in a sequential choice task. They found that greater interference on a Stroop task was negatively associated with the expression of model-based choice in the sequential choice task. That is, individuals that exerted greater cognitive control (and therefore showed less Stroop interference), also showed greater use of the deliberative model-based strategy. A similar association has been shown in a study by Eppinger et al. (2013). Here, greater working memory performance was associated with an increased use of model-based decision-making strategies (Eppinger et al., 2013). Importantly, although previous work has shown an association between model-based learning and cognitive abilities (Daw et al., 2011; Eppinger et al., 2013; Otto et al., 2015), it is not yet known, whether and how these complex goal-directed learning strategies relate to educational attainment.

Motivation and academic success

Aside from cognitive abilities there are many additional factors that are important for academic success, including motivation (Duckworth et al., 2019), and personality characteristics (Komarraju et al., 2009; Ruffing et al., 2015). In particular, the need for cognition (NFC)-

roughly defined as the willingness to engage in effortful behaviour (Cacioppo et al., 1984), has been positively linked to academic achievement (e.g., better GPA's or scores on standardized exams), as well as performance on intelligence tests (Cacioppo et al., 1996; Fleischhauer et al., 2010; Hawthorne et al., 2021; Neigel et al., 2017). NFC is assessed via a self-report questionnaire, with individuals judging themselves in response to various statements on their attitudes towards cognitive effort expenditure and level of engagement in mentally stimulating activities. Recent findings suggest that students who score high on NFC endorse positive attitudes towards problem-solving and high engagement in information processing (Colling et al., 2022). In general, these individuals seem to gain personal enjoyment by participating in cognitively effortful activities and are thought to be better able to handle mental stimulating tasks (Grass et al., 2017; Gray et al., 2015; Meier et al., 2014). By contrast, students with lower NFC report experiencing little enjoyment from intellectual engagement and prefer structured, feedback-based learning approaches with more assistance (Evan et al., 2003).

Although NFC has been shown to separately predict educational attainment (Hawthorne et al., 2021), as well as cognitive abilities (Hill et al., 2013), whether it interacts with cognitive abilities and higher-level goal-directed learning strategies and/or meta-control in supporting educational attainment remains to be determined. This hypothesis is supported by work from Sandra and Otto (2018) who found that individuals with lower Need for Cognition (NFC) exhibited greater reward sensitivity on a cognitive control task (i.e., task-switching paradigm). In contrast, individuals with high NFC exerted consistent cognitive effort irrespective of reward level, suggesting they were intrinsically motivated to perform well on the task. These findings support a cost-benefit account of cognitive effort expenditure (Yan & Otto, 2020), in which decisions to exert effort are influenced by the reward associated with that behaviour. According to this view, individuals with limited cognitive resources or low intrinsic motivation perceive greater costs to effort, and thus require higher external rewards to engage in cognitively demanding tasks. Conversely, those with higher capacity or motivation perceive lower effort costs and are less influenced by extrinsic incentives, as their engagement is sustained by internal value placed on mental effort.

Taken together, previous research has shown that different factors contribute to individual differences in educational achievement: Cognitive abilities such as processing speed, reasoning abilities and cognitive control play a role. However, the psychological mechanisms that mediate the relationship between cognitive abilities and educational attainment are unclear. It has also been shown that motivation and personality traits predict educational attainment. Yet, whether motivation interacts with cognitive abilities in supporting educational attainment, or whether it is an independent predictor of academic success remains to be determined.

Current Study

The aim of the current study is to examine the cognitive and motivational underpinnings of educational attainment in university students. That is, we would like to better understand how basic cognitive abilities and the intrinsic willingness to engage in effortful behaviour contribute to educational attainment. To gain insight into the psychological processes that may underlie the relationship between cognitive abilities, motivation, and educational attainment, we employed a computational reinforcement learning (RL) modeling approach in conjunction with a sequential learning task. This allowed us to examine how individual differences in learning strategies and motivational traits are associated with academic outcomes. Based on literature reviewed above we have the following predictions. First, we predict that there will be a positive relationship between cognitive abilities (i.e., reasoning abilities, processing speed, and attentional control), and educational attainment (Rohde & Thompson, 2007; Zisman & Ganzach, 2022). Moreover, given that previous work has shown that increased use of model-based learning strategies is associated with greater cognitive control (Eppinger et al., 2013; Otto et al., 2015), and stronger cognitive control abilities have been associated with better academic achievement (Duckworth et al., 2010; Duckworth et al., 2019; Richardson et al., 2012), we predict that greater use of these higher level learning strategies (as reflected in computational parameters) will be positively correlated with academic success. Additionally, like previous studies, we predict that model-based learning engagement (average MB weights) will be positively predicted by cognitive abilities (Eppinger et al., 2013; Otto et al., 2015). Next, we predict that there will be a positive relationship between the need for cognition and cognitive abilities (i.e., reasoning abilities, processing speed, and attentional control) (Hill et al., 2013). We also predict that the need for cognition will be positively correlated with educational attainment, consistent with work by Hawthorne et al. (2021) and Neigel et al. (2017). Although the NFC reflects a willingness or intrinsic motivation to engage in cognitively demanding tasks, recent work suggests that it is not associated with meta-control of decision-making (Bolenz et al., 2022). As such, we do not expect NFC to predict model-based learning engagement or meta-control of learning strategies.

Methods

Participants and Procedures

Participants were English-speaking, university students (undergraduate and graduate level) students between the ages of 18 and 30 years old at the time of the study. Individuals were excluded if they presented with a prior history of neurological illness, medications, auditory, visual or motor impairments impacting cognition and/or task performance. These conditions were screened for with an online questionnaire sent via email that included information about participants' medical, psychological, neurodevelopmental, academic (e.g., grades), and social history, as well as the need for cognition questionnaire. N=567 individuals completed this questionnaire. Of these, 540 individuals were deemed eligible and invited to participate in the main study. 214 young adults (157 females*)* (Mean age =21.9 y, SD=2.63) participated in the main study, which took place at Concordia University's Learning and Decision-Making Lab. Within this final sample (N = 214), all participants were fluent English speakers (as required for inclusion in the study), but their reported first languages varied. Just over half (56.1%) reported English as their first language, 18.7% reported French, and the remaining 25.2% reported a range of other mother tongues (e.g., Arabic, Spanish, Portuguese, Italian, Mandarin, Russian). With respect to academic load, most students were enrolled in four courses per semester (63.3%), followed by five or more courses (26.5%), three courses (8.2%), and two courses (2.0%). In terms of degree progression, 7.6% were in their first year of undergraduate study, 28.9% in their second year, 26.9% in their third year, 24.4% in their fourth year, and 12.2% had spent four years or more completing their undergraduate degree. Participants had an average GPA of 3.29 (SD = 0.58) and a mean high school average grade of 83.6% (SD = 6.71), based on available data. A small number of participants did not provide course-load or degree-progression information because they were graduate students at the time of the study. Of note, the sample size varied across analyses due to missing data. Each participant individually completed a battery of cognitive tasks taking an average of 2.75 h to complete. Up to four participants were tested simultaneously on individual computers. Participants were encouraged to take breaks between the tasks. Upon completion of the study, participants were compensated and debriefed. Students were compensated with undergraduate course credits in psychology or 25 Canadian dollars plus an additional amount of up to 15 dollars, depending on performance in the incentivized tasks. The Human Research Ethics Committee at Concordia University approved the study.

Materials and Measures

Cognitive Abilities. Participants were assessed individually on a battery of cognitive tasks measuring speed of processing, abstract reasoning (fluid intelligence), attention, and task-switching (cognitive control).

Speed of processing. Speed of processing was assessed using the identical pictures task (Ekstrom et al., 1976; Lindenberger et al., 1993). In this task, participants are presented with a series of trials in which they have to identify as quickly and as accurately as possible, which out of a set of five pictures is identical to a target picture. Speed of processing was calculated as the maximum number of correctly performed trials in the task.

Abstract reasoning. Abstract reasoning (or fluid intelligence) was assessed using the Raven's Progressive Matrices Short Form (Bors & Stokes, 1998). In this task, participants are presented with a series of visual patterns with a missing piece and are required to select the option that best completes the pattern from a set of alternatives. Performance was quantified as the total number of correctly completed matrices, reflecting the participant's nonverbal reasoning ability.

Attention. Sustained attention was assessed with the Conner's Continuous Performance Task (CPT) (Advokat et al., 2007). In this task, participants are presented with a rapid sequence of letters on a computer screen and instructed to press a key in response to every letter except for the target letter "X." The task requires participants to maintain focus and inhibit automatic responses. Performance on the CPT was quantified as the total number of correctly performed trials, which reflects general task accuracy and sustained attention over time. Although this composite does not distinguish between specific sources of error, such as lapses in attention or impulsive responding, overall accuracy reflects a combination of factors related to attention, including sustained focus, vigilance, impulse control, and general task engagement. Higher accuracy is therefore typically associated with more consistent attentional control across the task duration.

Cognitive control. To measure cognitive control abilities, we implemented an incentivized task-switching paradigm adapted from Sandra and Otto (2018) and Otto and Daw (2019). In this task, participants alternated between two classification tasks: a ***size*** task, where they judged whether an object was small or large, and a ***food*** task, where they classified the object as a fruit or a vegetable. Each trial began with a visual task cue (either "SIZE" or "FOOD") to indicate the relevant judgment. Critically, the task was incentivized: prior to each trial, participants were shown the number of points available for a correct response. They were instructed that earning more points would result in higher monetary compensation, with 100 points equivalent to $0.06. This manipulation created a dynamic reward environment designed to influence response vigor and cognitive effort. Participants completed the task under time pressure and were encouraged to accumulate as many points as possible within a 10-minute period. *Task-switching costs* were calculated as the difference in reaction time between switch and non-switch trials, reflecting cognitive flexibility and the efficiency of executive control. The greater the switch cost, the lower the cognitive control. The *reward rate effect* (i.e., reward rate sensitivity) was computed as the difference in accuracy between high-reward-rate and low-reward-rate trials, and reflects participants' ability to adjust performance in response to changing reward contexts.

Aggregate measure of cognitive abilities. An aggregate cognition score was computed (for the meditation analysis). This was done by averaging across the four measures of cognitive ability (speed of processing-total correct trials, abstract reasoning/fluid intelligence- total correct trials, attention-percent accuracy, and task switching costs).

Learning strategy. In addition to the cognitive measures, we asked participants to perform an incentivized sequential decision-making task that captures goal-directed learning and decision processes (Bolenz et al., 2022; Kool et al., 2017; see Appendix C). The task used in the present study was identical to that described in Bolenz et al. (2022) and represents an adaptation of the original paradigm introduced by Kool et al. (2017). On each trial, participants selected between two spaceships, each deterministically leading to one of two planets (red or purple) where a drifting reward was delivered. Because two different starting screens each contained spaceships that led to the same planets, a given planet could be reached through multiple paths. This structure enabled the dissociation of a model-free learning strategy, in which choices were repeated based on prior reward, from a model-based strategy, in which knowledge of the task structure was used to generalize across starting states leading to the same planet. Rewards on each planet followed independent random walks, requiring continuous updating of choice behavior. To examine meta-cognitive control, the stakes of the trials were manipulated: in low-stakes trials, rewards were multiplied by one, whereas in high-stakes trials, they were multiplied by five. This manipulation tested whether reliance on model-based versus model-free strategies varied as a function of potential payoff. Model-based weights (MB weights) are computational parameters that reflect the relative weight of the model-based learning strategy. MB weights were estimated separately for high- and low-stakes trials. An overall MB weight, reflecting the average reliance on model-based learning across conditions, was calculated as the average across conditions. Meta-cognitive control was indexed as the difference between MB weights in high- versus low-stakes trials (MB difference). Additional details regarding the computational modeling analyses are provided in Bolenz et al. (2022).

Cognitive effort engagement. The willingness to engage in effortful cognitive behavior was assessed using three different measures: The sensitivity to incentives in the decision task and the task switching paradigm as well as the need for cognition (NFC) questionnaire. The NFC was measured using the 18-item NFC scale (Cacioppo & Petty, 1982; Cacioppo et al.,1984). See Appendix D for the full questionnaire. All of these measures were z-transformed before including them in the regression analyses.

Academic achievement. Finally, educational attainment was assessed using self-report measures of average High school grades (HS) and cumulative undergraduate GPA (ucGPA). HS and GPA scores were z-transformed and averaged. The resulting score is in the following referred to as “educational attainment”.

Results

In the first analysis we used linear regression (via the lm() function in base R; versions 4.0.5 and 4.2.2) to examine whether any of the described measures significantly predicted educational attainment (as measured by combining undergraduate GPA and high-school average scores). These predictors include: the need for cognition, model-based decision-making average and difference scores, fluid intelligence/abstract reasoning (Raven’s Matrices total accuracy score), attention (continuous performance test percent accuracy), processing speed (identical pictures total correct), cognitive control (task-switching reaction time switch costs), and reward sensitivity, as well as age and gender as covariates. The results revealed a significant positive effect of need for cognition ($ß = 0.23$, $p < .01$) and model-based learning (average model-based weight) ($ß = 0.18$ $p < .05$) on educational outcomes.

None of the other variables significantly predicted grades (ß's < |.10|, p's > .11), including the model-based difference (which reflects meta-control). As shown in Figure 1.1, a greater engagement in model-based learning (Figure 1.1A) and a higher need for cognition (Figure1.1B) and a were associated with better educational attainment.

Next, in order to understand the potential differential contributions of the predictors on the different educational outcomes used in our study, we conducted separate regression analyses with high school average, and undergraduate grade point average as the dependent variables. Results reveal that NFC significantly predicts grades in both grade type analyses (GPA: ß=0.17, p< 0.05), HS: ß=0.31, p< 0.001), while effects for MB average are marginally significant / a trend for HS (ß=0.18, p=.057) but not significant for GPA (ß=0.14, p> 0.15).

In the next step we examined whether model-based learning or NFC scores were predicted by any of the other variables.

In the first analysis, with the MB average weight as a dependent variable, we found that fluid intelligence/abstract reasoning (ß = 0.13, p < 0.05) and attention (ß = 0.16, p < 0.01), significantly positively predicted model-based learning. Speed of processing (ß = 0.12, p < 0.055) was a marginally significant positive predictor of the model-based learning (see Figure 1.2). Thus, better performance on a variety of cognitive measures (notably, fluid intelligence and attention) was associated with a greater engagement in model-based learning strategies. None of the remaining variables significantly predicted model-based learning (ß's < |0.11|, p's > 0.08).

The second analysis revealed that fluid intelligence/abstract reasoning positively predicted NFC (ß = 0.16, p < 0.05), whereas reward rate effects in the task switching task were negatively associated with NFC (ß = -0.17, p < 0.05) (See Figure 1.3). Taken together, these findings suggest that the willingness to exert cognitive effort in cognitive control task, as well as fluid intelligence are associated with the need for cognition. None of the remaining variables significantly predicted NFC (ß's < |0.146|, p's> 0.1).

Discussion

The purpose of this study was to explore cognitive and motivational predictors of educational attainment in university students. In terms of cognitive predictors we assessed fluid intelligence, attention, processing speed and cognitive control as well as higher level meta-control and goal-directed learning strategies. With respect to motivational predictors, we examined the need for cognition (NFC)-reflecting an intrinsic motivation to engage in cognitively effortful tasks- as well as reward sensitivity and its interaction with cognitive engagement in an incentivized task-switching paradigm. Educational attainment in university was operationalized as cumulative undergraduate grade point average (GPA) as well as high school grades.

In short, we found that a greater engagement in goal-directed, model-based learning, and greater need for cognition were associated with better educational outcomes. In contrast, meta-control (operationalized as the difference in model-based weights between high- and low-stakes conditions (MBdifference))was not significantly associated with educational attainment. This suggests that it was not the strategic modulation of learning strategies based on reward context, but rather the overall tendency to engage in goal-directed learning (as reflected in average model-based weights), that related to academic success. These findings imply that consistent reliance on model-based strategies, regardless of what is at stake in a given task, may be more beneficial for long-term educational outcomes than selectively adapting effort in response to changing incentives. None of the other variables significantly predicted educational attainment. Subsequent analyses showed that model-based learning was significantly positively predicted by a set of cognitive abilities including fluid intelligence, and attention. NFC was also positively predicted by fluid intelligence and showed a negative association with reward sensitivity. Our findings indicate that the willingness to engage in mentally effortful activity, as well as the engagement in goal-directed learning strategies are important for educational success (in high school and university). Attentional capacity positively predicted the engagement in model-based learning and fluid intelligence was a consistent predictor of both the NFC and model-based learning above and beyond other cognitive variables. This suggests that it is a prerequisite for both, the ability to engage in goal-directed learning strategies and the willingness to engage in cognitively effortful behaviour.

Predictors of grades and academic achievement

Academic success has long been a focus of research due to its strong association with long-term personal and societal benefits, including greater financial stability, employment security, and job satisfaction (Baum et al., 2013; Carnevale et al., 2016; Ma & Pender, 2023). The identification of the key predictors of academic success is critical for understanding individual achievement. However, it is also important for informing evidence-based educational practices and developing targeted interventions to support student learning and retention across diverse educational settings.

The literature on academic success in students points to various predictors of educational attainment including but not limited to neurocognitive abilities, personality traits, motivational factors, mental health outcomes, and more (Malanchini et al., 2019; Tikhomirova et al., 2014; Tikhomirova et al., 2020; Zisman & Ganzach, 2022). Although both cognitive and motivational factors have been repeatedly shown to influence academic attainment across developmental stages and educational settings, the differential contributions of these cognitive and non-cognitive influences are still not well-understood. In the current study we investigated whether measures of cognitive abilities, the usage of higher-level goal-directed learning strategies and motivation differentially predicted academic performance in university students. The results showed that only two of the variables that we assessed in this study directly predicted educational attainment as reflected in high-school grades (HS) and undergraduate grade point average (ucGPA): The degree to which individuals engage in a goal-directed (model-based) learning strategy, and the self-reported willingness of individuals to exert mental effort i.e., need for cognition (NFC). The positive relationship between educational attainment and goal-directed learning strategies suggests that the ability to represent and navigate in complex task structures plays a role for success in higher education. By contrast, meta-control—the extent to which participants adjusted their learning strategy in response to changing reward incentives—was not related to academic outcomes. This finding may suggest that academic success depends less on selectively deploying cognitive effort depending on what is at stake in a given task and more on the consistent engagement in goal-directed learning and decision strategies, regardless of the potential incentive. In line with prior research, individuals with greater cognitive and motivational resources may engage in model-based learning even when the immediate payoff is low, reflecting a more stable and proactive cognitive style.

Given that this is the first study to look at the relationship between computational variables of learning and decision-making and educational attainment statements about the underlying translational mechanisms remain speculative. One first step towards a better understanding of this association might be to differentiate different programs or different subjects within a study program. The current sample is relatively homogenous (primarily psychology students). A greater heterogeneity in the study population and a greater differentiation in terms of the grades might help to shed more light on the obtained relationships between complex goal-directed learning strategies and educational outcomes.

The cognitive measures that we acquired (i.e., abstract reasoning, processing speed, cognitive control and attention) did not directly predict high-school nor university students' grades. This is inconsistent with previous work that showed direct links between performance on neurocognitive tasks and educational attainment (Dubuc et al., 2022; Malykh et al., 2017; Pascual et al., 2019; Peng & Kievit, 2020; Tikhomirova et al., 2020; Tikhomirova et al., 2021; Zisman & Ganzach, 2022).

Other studies however suggest that, while cognitive abilities and neurocognitive task performance are positively linked to academic performance, they do not always directly predict it (Keng, 2023). Other factors moderating the strength of this relationship, include factors such as age, culture, SES, and the structure and quality of the educational environment and curricula (Bjorklund-Young, 2016; Keng, 2023; Tikhomirova et al., 2019). For instance, the predictive power of cognitive abilities on academic achievement purportedly increases in educational settings that are more homogenous and academically rigorous (Tikhomirova et al., 2019; Zheng et al., 2019). In such contexts, where external support and instructional quality are relatively constant, individual differences in cognitive ability may play a more prominent role in determining outcomes. Other studies have shown that the influence of various cognitive abilities on academic attainment change with age (Peng & Kievit, 2020). Although the data is mixed, with some studies revealing stronger links between cognitive ability and academic performance in younger individuals (i.e., children compared to adolescents and young adults) (Follmer, 2017), while others show the opposite effect, with the relationship between cognitive ability and academic attainment strengthening with age (Peng et al., 2019).

Importantly, not all cognitive variables contribute equally to academic performance (Tikhomirova et al., 2020), though variables such as fluid intelligence are thought to be a more stable/pervasive predictor of educational achievement, across diverse settings and groups with correlation coefficients of ~0.37- 0.63 documented across the literature (Brouwers et al., 2009; Deary et al., 2007; Verbitskaya et al., 2020). With that being said, Zaboski et al. (2018) found that general intelligence ('g') explained the majority of variance in academic skills, whereas individual broad cognitive abilities- such as fluid and crystallized intelligence, processing speed, and memory- each accounted for less than 10%. In our study, we examined the unique contribution of fluid intelligence (as measured by Raven's Matrices) to GPA, independent of other cognitive and motivational factors. We found a small but statistically significant association, explaining approximately 2% of the variance in GPA. This modest effect suggests that while fluid intelligence contributes to academic performance, its predictive power alone is limited, highlighting the likely importance of other factors such as motivation, study habits, or executive functioning (Baars et al., 2015; Credé & Kuncel, 2008; Duckworth et al., 2010; Richardson et al., 2009; Richardson et al., 2012; Robinson, 2004; Shi & Qu, 2021; Shi & Qu, 2022; Zimmerman, 2011). These findings align with the view that the translation of cognitive potential into academic success is influenced by a broader set of individual and contextual influences.

Predictors of the engagement in model-based learning strategies

According to dual-process theories of reinforcement learning (Drummond & Niv, 2020; Kool et al., 2017), the ability to learn, choose, and execute decisions is guided by two strategies. The first is a habitual, or model-free approach that relies on learning stimulus-response associations based on reinforcement. Model-free reinforcement learning requires minimal cognitive effort. However, the downside of this strategy is that the learnt behavior is inflexible because new routines need be re-learned over many repetitions.

The second learning strategy is a goal-directed, model-based approach that involves learning the structure of a task. It comes with demands on cognitive resources but provides more flexibility in adapting to changes in environment because it relies on an internal representation. To make this more concrete, the learning and automatization of simple mathematical operations like addition or multiplication relies on reinforcement (feedback) and multiple repetitions. In contrast, knowing how these operations relate to each other and how to flexibly engage in these calculations relies on higher-level mental representations of the task structure.

Of the cognitive measures that we acquired, fluid intelligence/abstract reasoning (as measured by Raven's Matrices) and attention (as measured by the CPT), significantly positively predicted model-based learning behavior. This is consistent with previous studies that point to strong associations between basic cognitive abilities and model-based decision-making (Eppinger et al., 2013; Otto et al., 2015; Otto & Daw, 2019). For example, previous work has shown that difficulty with inhibition in a continuous performance test and Stroop task, is associated with a reduction in the utilization of model-based learning strategy on a separate decision-making task (Otto et al., 2015), This implies, that the mechanisms that underlie model-based learning and cognitive control may overlap. In addition, this same study (by Otto et al., 2015) demonstrated that greater use of a proactive response strategy (instead of the reactive execution strategy) on the AX-CPT predicts greater model-based engagement. While we could not assess proactive or reactive interference with our basic CPT task, our results do reveal a significant positive association between performance accuracy on the CPT (an aggregate measure of attention and cognitive control) and model-based behavioral engagement. These findings suggest that core cognitive abilities, particularly fluid reasoning and attentional control, play a role in supporting model-based learning strategies. However, more work is required to better understand the specific contributions of various basic cognitive processes to model-based behavior.

Predictors of NFC

Previous work has shown that greater cognitive performance is associated with a higher need for cognition (NFC) (Cacioppo et al., 1996; Evans et al., 2003; Fleischhauer et al., 2010). With that being said, it is unclear which aspects of cognition are most predictive of the NFC. Hill et al. (2013) assessed the relationship between NFC and different facets of intelligence. While the study found that both fluid and crystallized intelligence showed a significant positive relationship with need for cognition, working memory capacity was not associated with NFC. In the present study, we found that NFC was positively predicted by fluid intelligence. However, none of the other cognitive variables, including attention or processing speed showed significant positive associations, potentially suggesting that NFC may be more closely linked to higher-order reasoning abilities than to basic cognitive processes.

Various mechanisms by which NFC influences aspects of cognition have been proposed (Colling et al., 2022; Hill et al., 2013; Weissgerber et al., 2018). For instance, it has been hypothesized that those with a higher need for cognition show higher fluid intelligence due to greater task persistence on tasks of problem-solving (Hill et al., 2013). Gf tasks require abstract and systematic analysis as well as problem-solving ability, and it is possible that those with NFC persist more on such tasks due to a greater inherent interest and motivation in solving the types of problems. Although individuals with higher NFC tend to persist longer on problem-solving tasks, this persistence may have limited relevance for tasks measuring working memory, attention, or processing speed. It is possible that those high in NFC are predisposed to systematic and comprehensive analysis, a skill needed for fluid intelligence tasks that require abstract reasoning and problem-solving. However, this skill may be less advantageous for cognitive tasks that are more constrained by speed of processing.

For instance, the task we used to assess Gf in the current study had no time limit, and individuals could persist on the task for as long as they wanted. In fact, ancillary correlation analyses revealed that the more time participants spent completing the Raven's matrices in the current study, the better their performance. While NFC was correlated positively with Raven's Matrices accuracy score, there was no significant relationship between the completion time and NFC, which suggests that the association between NFC and fluid intelligence may not solely be due to the time spent on the task, but rather the quality of the cognitive engagement in combination with the time spent on the task. This is in alignment with the idea that high NFC individuals engage greater and more systematically on problem-solving tasks, which is why they perform better on tasks of fluid intelligence.

Unexpectedly, we found that the NFC was associated with effort expenditure in an incentivized (rewarded) cognitive control task. Effort expenditure in this task was operationalized as the willingness to engage in (effortful) cognitive control as a function of the average reward rate (how much reward you can get per unit time). The results suggest that individuals high on NFC are more willing to engage in effortful cognitive processing even if the average reward rate is low whereas individuals low on NFC are less willing to do so. These results suggest that the need for cognition predicts the actual expenditure of cognitive effort under different levels of incentives.

In conclusion, this study not only lends more support to the positive association between NFC and fluid intelligence, but also reveals a negative relationship between NFC and reward sensitivity on a task-switching paradigm. This suggests that individuals with higher NFC are less influenced by external rewards, potentially due to their higher intrinsic motivation towards cognitive tasks and a preference for accuracy over speed.

Limitations and future directions

While this study provides a comprehensive assessment of a range of factors, with a decent sample size, and use of objective measurement, computational modeling, and self-report, there are several limitations to consider when interpreting the results. The lack of a significant association between cognitive ability and GPA in this study raises broader questions about the extent to which GPA reflects true academic attainment. While GPA is commonly used as a marker of academic success, it may capture a range of influences beyond cognitive ability, including course difficulty, grading practices, motivation, and academic persistence. In our sample, which consisted primarily of female undergraduate psychology students, GPA was self-reported and drawn from students at various academic stages (i.e., ranging from freshmen to seniors and beyond), which may have further reduced its precision and comparability. Notably, many first-year students had not yet received a GPA, limiting our sample size. To supplement this, we also collected high school average grades, which were available for the full sample and potentially reflects performance across a broader range of academic domains (e.g., mathematics, language arts, science, and humanities). Interestingly, both Need for Cognition (NFC) and model-based control more strongly predicted high school grades than university GPA. This pattern may reflect the fact that GPA in our sample was drawn mainly from psychology courses and thus may not capture the full range of cognitive and motivational demands typically associated with academic attainment.

Taken together, these findings emphasize the importance of critically evaluating what GPA represents, highlighting the need for more comprehensive and standardized indicators of academic achievement in psychological research. It could also be argued that the cognitive and decision-making tasks lacked sufficient difficulty or sensitivity to differentiate individual performance. This is supported by the negatively skewed distributions and ceiling effects observed in participants' scores on the CPT, model-based, and task-switching tasks, suggesting that many participants performed near the top of the scale. When tasks are not sufficiently challenging, they may fail to capture meaningful variability in cognitive ability or decision-making style, thereby reducing the likelihood of detecting associations with academic outcomes.

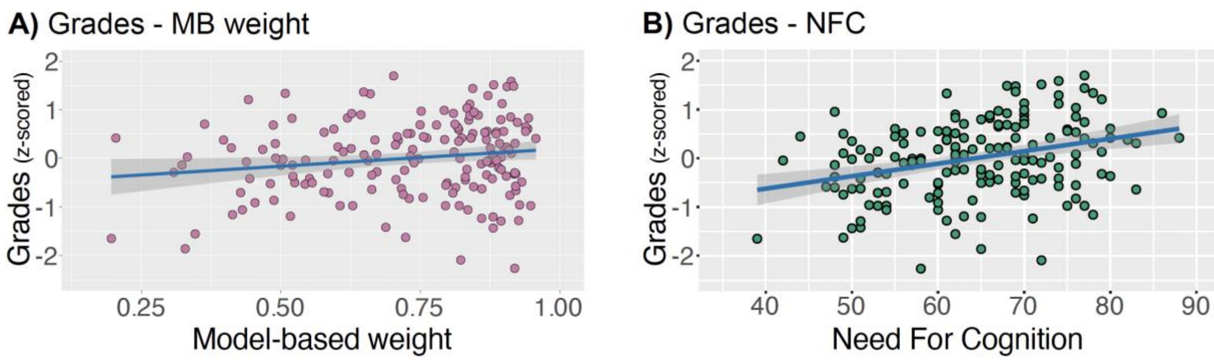
Future studies should consider using more challenging or adaptive task designs, in which difficulty dynamically adjusts based on a participant's performance. Embedding an adaptive learning structure within the task paradigm would help maintain continuous engagement and present an optimal level of challenge across individuals. This approach would allow for a more accurate assessment of a wider range of cognitive abilities and reduce the risk of ceiling effects that constrain interpretability.

Conclusions

This study found that both Need for Cognition (NFC) and higher-level learning and decision strategies were positively associated with academic performance. In contrast, cognitive abilities such as fluid intelligence, attention, processing speed, cognitive control as well as meta-control of learning did not significantly predict grades. These findings suggest that motivational traits and the overall engagement in goal-directed learning strategies may play a more central role in educational attainment than basic cognitive abilities and meta-control, at least within this homogenous sample of undergraduate students. To our knowledge, this is the first study to examine the motivational and cognitive underpinnings of academic success using computational methods in combination with experimental cognitive tasks and self-report. The findings highlight the potential of the computational approach in capturing learning and decision strategies and how they relate to academic achievement. However, our results also show that rather "simple" self report measures like NFC can provide important insights into the complex interplay of factors determining academic outcomes. Together, these findings emphasize the importance of looking beyond basic cognitive skills alone and consider how individual differences in motivational traits and goal-directed learning strategies contribute to educational success.

Figure 1.1

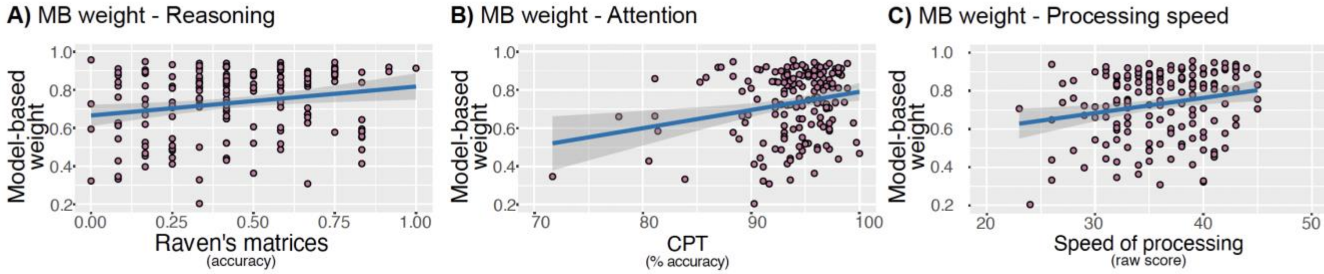
Predictors of Grades



Note. The scatterplots show the relationship between academic performance (z-scored average of undergraduate GPA and high school grades) and the average model-based weight (MB weight) as well as the need for cognition (NFC). (A) Significant positive association between MB weight and academic performance. (B) Significant positive relationship between Need for Cognition (NFC). Regression lines are plotted with 95% confidence intervals.

Figure 1.2

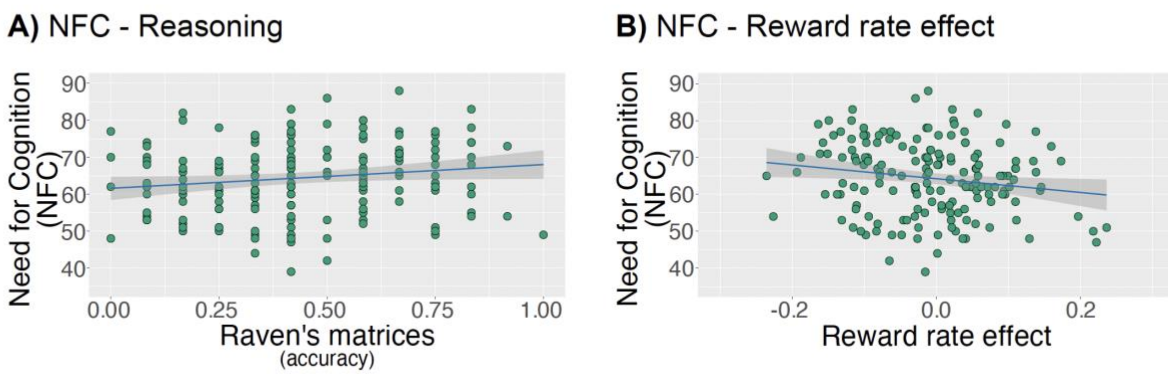
Predictors of Model-Based Weights



Note. The Figure shows the association between different cognitive variables and the model-based learning strategy engagement (MB weight). (A) The scatterplot shows a significant positive association between fluid intelligence, as measured by Raven's Matrices accuracy, and MB weight. (B) Illustrates a significant positive relationship between sustained attention (CPT percent correct) and MB weight. (C) Depicts a trend-level association between processing speed (identical pictures task) and MB weight. Regression lines are plotted with 95% confidence intervals.

Figure 1.3

Predictors of the NFC



Note. The Figure displays the association between cognitive and motivational variables and the need for cognition (NFC). (A) The scatterplot shows a significant positive association between fluid intelligence (accuracy on the Raven's Matrices) and NFC scores. B) The scatterplot illustrates that reward rate effects on a cognitive control task significantly negatively predict NFC. Regression lines represent fitted linear models with 95% confidence intervals.

CHAPTER THREE:

STUDY 2

Impact of the COVID-19 Pandemic on mental-health and academic performance in Canadian university students

Abstract

The COVID-19 pandemic has caused disruptions to the educational system since its onset in March 2020, leading to school closures and shifts to remote learning, inconsistent access to educational resources, as well as increased stress and mental health problems for both students and educators alike. These challenges have contributed to learning losses and declines in academic performance at the secondary school level. Data on the pandemic's impact on post-secondary learning outcomes is less consistent, with some studies reporting increases in academic performance, while others report declines. Thus, the purpose of this study is to investigate the pandemic's impact on university students' academic, mental and psychosocial functioning. Utilizing longitudinal data collected prior to the pandemic (from March 2019 to March 2020), and one year into the pandemic (March 2021-April 2021), we analyze changes in GPA, mental well-being, substance use, social networks, and subjective socioeconomic status. Additionally, we examined the predictors of educational attainment and substance use during the pandemic. Results show that while student's GPA increased during the pandemic, social networks, and reported well-being decreased, while substance use increased. Substance use turned out to be the only significant predictor of academic performance during the pandemic, while all other indices of mental health- including general anxiety and depressive symptoms as well as stressors unique to the pandemic- were not significantly related to academic outcomes. Notably, changes in substance use from before and after the pandemic's onset were significantly predicted by pre-existing mental health conditions suggesting that individuals with mental health challenges were more vulnerable to increased substance use and maladaptive coping during this period. Overall, these findings highlight the need for increased resources to support students' mental health and coping skills during crises, particularly for those with existing mental health vulnerabilities, which in turn can foster academic success and mitigate disruptions to their educational progress.

Introduction

The COVID-19 pandemic has had devastating global consequences, resulting in disruptions to economic, health, psychosocial, occupational, and educational sectors worldwide (Conroy et al., 2021; Cullen et al., 2020; Hu et al., 2022, Li et al., 2020; Lowe et al., 2023a; Lowe et al., 2023b; Wang et al., 2020; Yang et al., 2020). Residual effects of the pandemic are still present to this day, while the longer-term impacts will remain unknown for many years to come (Hu et al., 2022). The pandemic's impact on the educational sector has been a particular area of concern, with school closures and the transition to remote learning fundamentally altering the academic experiences of students and raising concerns about their progress and mental well-being (Lowe et al., 2023a).

Impact of the pandemic on educational attainment

In March 2020, schools across Canada closed temporarily in response to the COVID-19 pandemic to limit the spread of the virus. Closures were initially set for two weeks but extended as the pandemic progressed. The schools responded with a shift towards remote learning, online classes and other distance learning methods. However, several studies now suggest this shift negatively impacted students' academic progress and mental health (Aristovnik et al., 2020; Aucejo et al., 2020; Borgaonkar et al., 2021; Cao et al., 2020; Haynes et al., 2024; Hu et al., 2022; Mahdy, 2020; Sauer et al., 2022).

The degree to which the pandemic's affected academic outcomes varies across studies, depending on the student population being studied. In elementary age students (grades 3-8), math and reading grades declined one year into the pandemic (Fall 2021), compared to same grade students prior to the pandemic (Fall 2019) (Kuhfeld et al., 2022). In college students, results are mixed (Ferrar et al., 2023; Karadag, 2021), with some authors reporting a reduction in student academic performance (Borgaonkar et al., 2021; Haynes et al., 2024; Mahdy, 2020), while others report that students' grades actually improved or maintained relatively stable during the COVID lockdown (Clark et al., 2021; LaGuardia Community College, Office of Institutional Research and Assessment, 2022).

A study by Ferrer et al. (2023) examined specific factors that affected university student grades during the pandemic. They found that students who positively evaluated online and remote instruction had better academic performance than those who negatively rated remote learning. Thus, students who had an easier time adapting to online learning were more likely to perform better in school. Conversely, students who suffered more from the mental and physical health consequences of COVID-19 and had less access to technological resources performed worse academically during the pandemic. It should be noted that the measure used to describe academic performance in this study was a latent variable reflecting students' perceptions of how the pandemic impacted their performance, rather than an objective academic measure. By contrast, a report by LaGuardia Community College, Office of Institutional Research and Assessment (2022) provided objective data on the pandemic's impact on academic outcomes in community college students, such as changes in enrollment, retention rates, and coursework GPA. The results suggest that first-year enrollment rates declined more in lower-income and minority students compared to those with greater socioeconomic advantage. Nevertheless, for the majority of first-year courses, student pass rates and course completion rates remained comparable to pre-pandemic statistics. GPA for English courses declined during the pandemic compared to the two semesters pre-pandemic, while GPA for mathematics courses actually increased. Additionally, consistent with other studies in the U.S. (Ferrer et al., 2023), most students in the report by LaGuardia Community College, Office of Institutional Research and Assessment (2022) described feeling satisfied with their professors and courses but rated their online learning experiences less favorably than in-person teaching (Mahdy, 2020). Taken together, these findings suggest that the impact of the pandemic on educational attainment varied significantly across studies, with disparities potentially influenced by factors such as age and level of education, subject type and/or degree, socioeconomic status (SES), and adaptability to remote learning.

Why did the pandemic impact student education?

As described above, the COVID-19 pandemic has impacted student academic outcomes to varying degrees (Borgaonkar et al., 2021; Clark et al., 2021; Fahle et al., 2023; Haynes et al., 2024; Kuhfeld et al., 2022; Kuhfeld et al., 2023; LaGuardia Community College, Office of Institutional Research and Assessment, 2022; Mahdy, 2020; Vautier et al., 2023), however the specific reasons for these changes remain unclear. In particular, mental health challenges have been a growing area of concern, given the pandemic's widespread psychological toll on both the general population and student communities (Aristovnik et al., 2020; Cao et al., 2020; Copeland et al., 2020; Cullen et al., 2020; David et al., 2022; Fruehwirth et al., 2025; Hu et al., 2022; Pfefferbaum et al., 2020; Sauer et al., 2022; Xiong et al., 2020). And given that mental health problems are highly prevalent in college students (Center for Collegiate Mental Health, 2020; Eisenberg et al., 2009; Evans et al., 2018; Jao et al., 2019; Lui et al., 2019), and a common cause of academic challenges and college attrition (Auerbach et al., 2016; Son et al., 2020), the exacerbation of psychological stress during the pandemic raises important questions about how this may have influenced students' academic performance.

Various pandemic-related factors have been hypothesized to contribute to mental health problems. For instance, studies have found that mass-confinement directives led to reduced social connection and increased loneliness (Banerjee & Rai, 2020; Jeffers et al., 2022; Lowe et al., 2023b), as well as heightened anxiety and depressive symptoms (Li et al., 2020). Additionally, substance use, and deaths related to substance also rose significantly during the pandemic, potentially as a consequence of this isolation related to confinement (Charles et al., 2021; Dumas et al., 2020; Pelham et al., 2021; Vo et al., 2022; Wainwright et al., 2020). In university students specifically, Charles et al. (2021) found that rates of substance use (largely alcohol use) along with symptoms of anxiety and depression increased significantly during the initial period of the COVID-19 pandemic (in Spring 2020). Alarmingly, similar trends were noted in adolescents (high-school students), with the frequency of alcohol and cannabis consumption increasing (Dumas et al., 2020; Pelham et al., 2021). Interestingly, Dumas et al. (2020) found that the actual percentage of substance users decreased, but those that maintained their use showed *greater* rates of use during the pandemic.

Importantly, studies have shown that individuals with pre-existing mental health issues had greater difficulty coping with their stress during the pandemic (Czeisler et al., 2020; Lowe et al., 2023a). For example, college students with greater symptoms of anxiety and depression were more susceptible to pandemic related stressors and at greater risk for adverse psychosocial outcomes during the pandemic (Li et al., 2020). Other work revealed that greater rates of depressive symptoms and anxiety associated with contracting COVID-19 infection predicted increases in solitary substance use (Dumas et al., 2020). This is problematic since solitary substance use during the pandemic was associated with increased overdose related deaths (Ghose et al., 2022; Rosen et al., 2023). With that being said, it remains unclear how such vulnerabilities (i.e., increases in substance use and worsening mental health) affected students' educational attainment over the pandemic. These findings highlight the broader impact of the pandemic on student well-being, particularly for those already facing mental health challenges. However, the effects of the pandemic were not experienced equally across all student populations (Reyes-Portillo et al., 2022). Certain groups, including minority and lower SES students, faced unique stressors that further compounded their mental health struggles and academic challenges (Aucejo et al., 2020; Fahle et al., 2023; Reyes-Portillo et al., 2022). For instance, one study by Reyes-Portillo et al. (2022) showed that the mental health of minority students were more likely to be negatively impacted by academic, financial, and COVID-related stressors, compared to non-minority individuals. Worries about being infected with COVID-19, inadequate living conditions, poorer academic performance, and lack of social support/loneliness were all associated with worsened mental health during the pandemic (Reyes-Portillo et al., 2022). Individuals from lower socioeconomic backgrounds not only faced substantially more financial hardship during the COVID-19 pandemic than their higher-SES counterparts, but also reduced access to technological and educational resources, greater vulnerability to COVID-related health issues due to inadequate health care coverage, as well as greater mental health difficulties (Aucejo et al., 2020; Kuhfeld et al., 2022; Kuhfeld et al., 2023; Parker et al., 2020; Reyes-Portillo et al., 2022).

Purpose and aims of the current study

The COVID-19 pandemic upended traditional schooling, leading to extended periods of remote learning, inconsistent access to educational resources, and increased stress and mental health problems for both students and educators alike (Aucejo et al., 2020; Clemmons et al., 2022; Dumas et al., 2020; Harding et al., 2023; Reyes-Portillo et al., 2022; Zamarro et al., 2022).

Although prior research has well-documented the exacerbation of mental health issues among college students during the COVID-19 pandemic, especially in its early stages (David et al., 2022; Fruehwirth et al., 2025; Sauer et al., 2022; Son et al., 2020), and a negative relationship between mental health problems and academic attainment was already well-established prior to the pandemic (Maghalian et al., 2023; Son et al., 2020), the extent to which pandemic-related mental health challenges directly influenced students' academic performance remains unclear. Given the widespread concern about how the COVID-19 pandemic has disrupted both mental health and academic performance, potentially in ways that may affect long-term workforce readiness and societal functioning at large (Aucejo et al., 2020), it is important to examine the underlying psychological and contextual factors contributing to these outcomes. Our study provides longitudinal data obtained at timepoints prior to the pandemic (the pre-pandemic data spanning a timeframe from March 2019 to March 2020), and one year following the pandemic's onset and the corresponding lockdown (March 2021 to April 2021) (see Figure 2.1 for the study timeline procedure).

Predictions

Based on prior studies (Borgaonkar et al., 2021; Ferrar et al., 2023; Haynes et al., 2024; Mahdy, 2020) we predict that participants' GPA will be significantly affected by the pandemic, in that we predict that there will be a reduction in GPA acquired at T2 (during the pandemic) relative to T1 (pre-pandemic). Next, we predict that there will be a significant reduction in various psychosocial outcomes including participants' social networks, and SES, accompanied by a rise in substance use, and poorer mental well-being in line with several studies that show changes in these outcomes during the pandemic (Banerjee & Rai, 2020; Charles et al., 2021; Czeisler et al., 2020; Jeffers et al., 2022; Li et al., 2020; Lowe et al., 2023b; Parker et al., 2020; Vo et al., 2022; Wainwright et al., 2020). As suggested by work from (Columb et al., 2020;Volkow et al., 2020), we predict that poorer mental health before the pandemic (i.e. individuals with psychiatric diagnoses pre-pandemic) may be linked to a rise in substance use during the pandemic. Finally, in line with prior studies that show negative relationships between mental health outcomes and academic attainment (Auerbach et al., 2016; Maghalian et al., 2023; Son et al., 2020), we hypothesize that mental health measures, including: general anxiety and depressive symptoms, as well as a rise in substance use will have significant influences on GPA during the pandemic (at T2).

Methods

Study Rationale and Context

This study emerged as an unexpected but valuable opportunity in response to the COVID-19 pandemic. Initially, in a first study prior to the pandemic, we set out to examine a range of factors influencing students' educational outcomes, collecting extensive data on cognitive, motivational, demographic, academic, social, psychological and socioeconomic variables. However, when the pandemic struck, it became clear that this unprecedented global event was likely to impact students' academic, mental, and psychosocial functioning. Recognizing the significance of these changes, we sought to examine how students' experiences and outcomes evolved over time by conducting a follow-up assessment at a second time point (T2). This allowed us to explore changes in educational attainment, mental health outcomes, social networks, and socioeconomic status, while also incorporating new variables relevant to the pandemic context. In short, given the extensive dataset collected in the first study, we recognized the unique opportunity to reassess participants at a second time point (T2) and examine how key predictors from the first study may have been influenced by the pandemic. This allowed us to investigate changes in educational attainment and related outcomes while also incorporating new variables specific to the pandemic context. The unplanned nature of this second study thus enabled an in-depth exploration of both stability and change in students' academic and psychosocial experiences in response to a large-scale disruption.

Participants and procedures

The longitudinal data for this study are from a previous study conducted during March 2019 to March 2020, the aim of which was to examine cognitive and non-cognitive (i.e., personality characteristics) predictors of educational attainment in college students. During this timeframe (T1), N = 567 university students completed an online questionnaire which included questions on participant demographics, socioeconomic status, medical and mental health history, high school and college academic performance, cognitive effort engagement, social networks, and drug use. Participants were excluded if they presented with a prior history of neurological disease, auditory, visual and/ or motor impairments. N = 540 individuals met inclusion criteria and were invited to participate in the main study at T1. For more details surrounding T1 protocol, see Chapter 2 of this dissertation.

For the present study, in order to assess the academic, social, and mental health impact of COVID-19 on university students, participants from T1 were recontacted during the pandemic to complete the original survey with additional measures to address pandemic related stressors. N = 133 students from the original sample completed the (T2) online questionnaire between March 2021-April 2021, approximately one year into the COVID pandemic. At this time, in-person classes remained limited, with the majority of learning taking place via on-line platforms, and social distancing recommendations in place due to rising COVID cases during the third wave of the pandemic. N = 8 individuals were removed due to incomplete responses. Thus, the final sample consisted of 125 university students (96% undergraduate + 4% graduate) attending Concordia University in Montreal, Quebec. Participants were between the ages of 18-30 years old (Mean age=24.1 years, SD=4.5), and 84% female (N=105 female). The sample consisted of 67% self-identifying as White or Caucasian, 9% Asian, 9% Middle Eastern or North African, 6% Hispanic or Latino, 4% Black or African-Canadian, 5% Other/chose not to answer. Year in college was non-equally and randomly distributed from sophomores (2nd year) to senior year (4th year) and beyond, with 20% reporting to be in their sophomore year, 30% in junior year, 30% in senior year, 10% in fifth year and beyond, 10% chose not to answer. 100% of the sample had access to a computer with internet in their home during the pandemic. The survey was administered electronically and took approximately 1 hour to complete. Electronic Consent from each student was obtained at the beginning of the online questionnaire. Upon completion of the study, participants were compensated with undergraduate course credits in psychology or awarded an amazon gift card. The Human Research Ethics Committee at Concordia University approved the study.

Materials and Measures

See Table 2.1 for descriptive statistics, including the range, mean and standard deviation for the variables described below. Figure 2.1 provides a timeline overview of the studies and the variables assessed at both timepoints.

MEASURES ACQUIRED AT BOTH T1 AND T2:

Academic achievement: Educational attainment was assessed at T1 and T2. The ucGPA used at T1 reflects students' self-reported grades at different timepoints (including ucGPAs provided in Fall 2018, Winter 2019, Spring-Summer 2019, Fall 2019), given the studies' one-year-long timeframe (March 2019-March 2020). In contrast, the ucGPA used at T2 reflects students' self-reported grades at one single time point, Fall 2020, at the height of the pandemic and online-learning was taking place. See Table 2.1 for descriptive statistics. Change scores were computed as the difference between T2-T1 for each participant (for within subjects analysis) participants ucGPA. The change score reflects changes in an individual student's trajectory across school years, rather than changes across cohorts of students at the same education level/year of university.

Social Networks: Information regarding social networks were assessed at both T1 and T2 using the Luben Social Network Scale (LSNS-6; Luben et al., 2006). The scale measures the number, frequency, and perceived social support received by social contacts including family members and friends. There are six total items which are rated on a six point Likert scale where respondents rate the extent to which they agree with each statement regarding the size, closeness, and number of contacts of an individual's social network, from None (0), One (1), Two (2), Three or Four (3), Five through eight (4), and Nine or more (5). There are three different statements which are repeated twice: one for Family members (**"***Considering the people to whom you are related, either by birth or marriage"),* and for non-related persons/ friends (**"***Considering all of your friends, including those who live in your neighborhood").* Sample statements include: "*How many of your friends do you see or hear from at least once a month?" "How many family members do you feel at ease with that you can talk about private matters?"* A total social engagement score was computed by adding the values participants endorsed from all scales. See Table 2.1 for descriptive statistics, including the range, mean and standard deviation for social networks scores, at Timepoints 1 and 2. A change score was computed as the difference between the T2-T1 total social engagement score for each individual participant.

Drug Use: Participants' consumption of substances was quantified with the *Alcohol, Smoking and Substance Involvement Screening Test (*ASSIST*;* WHO ASSIST Working Group, 2002). This data was acquired at T1 and T2. The instrument comprehensively screens for individuals' use of alcohol, tobacco and other psychoactive substances including: cannabis, cocaine, amphetamines, sedatives, hallucinogens, inhalants, and opioids, providing information on: the substances people have ever used in their lifetime; the substances they have used in the past three months; problems related to substance use; risk of current or future harm; dependence; injecting drug use. Participants rate their a.) Frequency of use; b) Desire or urge for the substance ; c) whether drug use has led to problems (i.e, health, social, legal, or financial); d) whether the drug use has caused failure to do what is normally expected of the person, <u>in the last three months,</u> responding with: Never, Once or Twice, Weekly, Monthly, Daily or Almost Daily. A total score was computed for each category of substance and separately for the four domains (a, b, c and d) mentioned above. See Table 2.1 for descriptive statistics including the range, mean and standard deviation for drug use scores, at Timepoints 1 and 2, and Supplemental Table A.1 in Appendix A for descriptive statistics of drug types. A change score for the total *drug use* score was computed as the difference between T2 -T1 for each individual participant.

Subjective Socioeconomic Status: In addition, participants were evaluated on their perceptions of their own social status relative to other individuals in the same geographical area using the MacArthur Scale of Subjective Social Status (Adler et al., 2000; Moss et al., 2023). This scale provides a rating of subjective SES on a scale from 1 to 10, with 1 being the lowest perceived social status/quality of life, and 10 being the highest social status/quality of life: "We are interested in how you perceive your life. Think of a ladder representing where people stand in North America. At the top of the ladder are the people who are the best off -- those who have the most money, the most education, and the most respected jobs. At the bottom are the people who are the worst off -- who have the least money, least education, and the least respected jobs or no job. The higher up you are on this ladder, the closer you are to the people at the very top the lower you are, the closer you are to the people at the very bottom. Imagine this rating scale represents the ladder. Where would you place yourself, relative to other people in North America?" ['1, very low on the social ladder', '2', '3', '4', '5', '6', '7', '8', '9', '10, very high on the social ladder']. This was assessed at both T1 and T2, and a change score was generated by calculating the difference in subjective SES ladder score at T2-T1.

Objective socioeconomic status (SES) Timepoint 1:*Parent's income:* To assess the financial stressors of the pandemic, we asked students to roughly approximate their parents weekly income across the following categories/ranges: '< 600$', '700-850$', '851-1000$', '1001-1150$', 1151-1300$', 1301-1450$', 1451-1600$', '1601-1750$', '1751-1900$', '1901$ +'. See Table 2.1 for descriptive statistics.

Objective socioeconomic status (SES) Timepoint 2: *Parent's income:* To assess the financial stressors of the pandemic, we asked students to roughly approximate their parents weekly income across the following categories/ranges: '< 100$', '101-200$', '201-300$', '301-400$', '401-500$', '501-600$', '601-700$', '701-800$', '801-900$', '901$ +'. See Table 2.1 for descriptive statistics.

Mental health:

Psychiatric diagnosis: Participants were asked about psychiatric diagnoses (pre-pandemic) at T1, including but not limited to: Mood disorders (Major depressive disorder, bipolar disorder), Anxiety disorders (generalized, panic, post-traumatic), eating disorders, sleep disorders, and psychotic disorders. The categorical variables were coded 0 =no psychiatric diagnosis pre-pandemic, and 1 = psychiatric diagnosis pre-pandemic. For a detailed breakdown of diagnoses, including the number of participants reporting a primary diagnosis and co-morbid conditions, refer to Supplemental Table A.2 in Appendix A.

MEASURES ACQUIRED AT ONLY T2:

Mental health and well-being: To examine changes in mental health, we administered well-validated questionnaires to assess symptoms of depression and anxiety. Participants were also asked to provide a retrospective rating of their well-being (prior to the pandemic), and current rating of their well-being (during the pandemic).

The *Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977)* is a 20-item self-report questionnaire used to measure the frequency and severity of depressive symptoms (such as mood, sleep disturbances, and appetite changes, over the past week). Participants were asked to rate their symptoms on a Likert scale, from **0** (Rarely or none of the time (less than 1 day)) to **3** (Most or all of the time (5-7 days)). Internal consistency is consistently high in U.S. and Canadian community-based samples (α = .85–.94; Johnson et al., 2008; Radloff, 1977; Roberts et al., 1989), and comparable values have been reported in university populations across multiple countries (α = .89–.92; Jiang et al., 2019; Shean & Baldwin, 2008). Test‑retest reliability is moderate, consistent with its sensitivity to current depressive states ($r \approx .50$‑.67 across 2‑8 weeks; Radloff, 1977). Convergent validity has been demonstrated through moderate to high correlations with other validated measures of depression including the Beck Depression Inventory (r=-.89), and clinical interview ratings of depression (Ogles et al., 1988; Radloff et al., 1977; Weissman et al., 1977). Evidence for criterion-related validity has also been shown in a U.S. college sample, where CES-D scores predicted DSM-IV diagnoses of depression (González et al., 1997). The total score ranges from 0 to 60, with higher scores reflecting greater symptom severity. A cutoff of ≥16 is widely used to indicate individuals at risk for depression, though higher cutoffs (e.g., 20–21) have been suggested for college student samples (Shean & Baldwin, 2008; Vilagut et al., 2016). The total score at T2 was used in the analysis as a measure of depressive symptoms. See Table 2.1 for descriptive statistics.

The *Beck Anxiety Inventory (BAI; Beck et al., 1988)* is a 21-item self-report inventory used to measure symptoms of anxiety. Respondents are asked to rate how much they have been bothered by a common symptom of anxiety (i.e. "numbness or tingling"), over the past one week on a scale from **0 (not at all) to 3 (severely).** The BAI demonstrates excellent internal consistency in clinical and community samples ($\alpha \approx .92$) and good short-interval test–retest reliability over one week ($r = .75$; Beck et al., 1988). In nonclinical undergraduate populations, internal consistency remains strong, though the BAI tends to function more as a state measure, with somewhat lower stability across time (Creamer et al., 1995). Convergent validity is robust with other anxiety scales, and discriminant validity is supported by weaker correlations with depression measures (Creamer et al., 1995). The total score indicates the severity of anxiety symptoms. Scoring guidelines indicate that scores of 0–7 reflect minimal anxiety, 8–15 mild anxiety, 16–25 moderate anxiety, and 26–63 severe anxiety. Scores of 16 or higher are often considered clinically significant, warranting further evaluation, though the BAI is not a diagnostic tool (Beck et al., 1988). See Table 2.1 for descriptive statistics for the present study.

Well-being: Participants were asked to rate their well-being both prior to the onset of the pandemic (i.e., "Please rate your general well-being before the onset of the pandemic") and during the midst of the pandemic (i.e., "Please rate your current general well-being"), on a scale of 1-100. Higher scores correspond to greater well-being. A change score was generated to reflect change in well-being due to the pandemic. See Table 2.1 for descriptive statistics.

Functional impact of pandemic: To better understand how the pandemic impacted participants' functional impairment, the Work and Social Adjustment Scale (WSAS)-a 5-item self-report measure of functioning across various life domains- was given to participants. The original WSAS was developed to screen for functional impairment secondary to psychiatric disorders such as depression, anxiety or substance misuse (Mundt et al., 2002). A revised version adapted for the pandemic (Lee, 2020) was used to better assess how the COVID-19 pandemic has impacted participants' 1) work or studies, 2) home management, 3) social leisure activities, 4) private leisure, and 5) relationships. Each item is rated on a 9-point Likert scale from 0 (not at all) to 8 (very severely). A sample item is as follows: *"Because of the pandemic, my ability to complete my academic work is impaired".* The total score provides an indication of overall functional impairment and helps in monitoring the impact of interventions and treatments. A total summary score was generated. The greater the score the greater the functional impairment. See Table 2.1 for descriptive statistics.

COVID-19 Related anxiety and Stress: Two measures were administered to quantify the degree of pandemic-related anxiety and stress felt by participants.

The *Coronavirus Anxiety Scale (CAS)* is a 5-item self-report tool designed to measure anxiety associated with the COVID-19 pandemic (Lee, 2020; Riepenhausen et al., 2020). Items are rated on a 5-point Likert scale from 0 (not at all) to 4 (nearly every day), over the past 2 weeks, evaluating symptoms including dizziness, sleep issues, appetite loss, and nausea. A sample item from the questionnaire includes: *"I felt dizzy, lightheaded, or faint, when I read or listened to news about the coronavirus."* A total score of 9 or higher suggests significant COVID-related anxiety. The psychometric properties of the CAS have been determined in various studies (Ahn et al., 2020; Choi et al., 2022; Lee, 2020). See Table 2.1 for descriptive statistics.

The *Perceived Stress Scale (PSS; Cohen et al., 1983)* adapted for COVID-19 (PSS-10-C; Campo-Arias et al., 2020; Gadermann et al., 2020) was used to measure stressors associated with the pandemic. The PSS used in this study contains 10- items, which assess general and pandemic-specific stressors. Participants are required to rate their level of stress for each item on a 5-point Likert scale, from 0 (Never) to 4 (Very Often), on items such as: "I have felt unable to cope with the things I have to do to control possibly being infected"; "I have been nervous or stressed by the pandemic"; "I have been confident about my ability to handle my personal pandemic related problems". Total scores were generated, with higher scores reflecting higher levels of perceived stress. See Table 2.1 for descriptive statistics.

Supplemental Academic Experience Measures: In addition, we acquired measures for satisfaction with academics, professor flexibility, and change in online academic activity, which are described in Appendix A (Supplemental Table A.3).

Statistical Data Analysis

All data were analyzed using R (version 4.2.2). The lme4 package was used to compute multiple linear regressions to determine the relationship between the predictors and outcome (GPA) (Bates et al., 2014). Paired-*t* tests were used to examine the changes in ucGPA, drug use, social network, and subjective SES between T1 and T2 measures, as well as the change in well-being during the pandemic and pre-pandemic (both as assessed at T2). Separate linear regression analyses were conducted to explore the factors associated with the change from T1-T2 in ucGPA and substance use, as well as ucGPA at T2. For change regression models, predictors included: change in drug use, change in social network size, change in subjective SES, change in well-being, and pre-existing psychiatric diagnosis (See below for the specific predictors for each regression model). The independent variables included in the regression models at T2 included: general anxiety symptoms (BAI total score), general depressive symptoms (CESD total score), functional impairment total score, anxiety specifically related to the covid infection and the pandemic, perceived stress score, social network total score, drug use total score, objective SES (parent income), subjective SES, pre-existing psychiatric diagnosis, change in well-being, academic satisfaction, flexibility of professors, percent change in academics happening online, controlled for age, sex and the score of the dependent variable. See below for the specific predictors for each regression model. Years of study were not controlled for. Of note, the sample size varied across analyses due to missing data.

Results

(1) Change in GPA, drugs, social network, SES subjective, and well-being

First, paired-samples t-tests were conducted to examine whether there are significant changes in undergraduate cumulative grade point average (cGPA), drug use, social networks, and subjective SES between T1 (before the pandemic) and T2 (during the pandemic), and retrospective change in well-being. As shown in Figure 2.2A participants' cGPA increased significantly from T1 (before the pandemic) to T2 (during the pandemic), $t(111) = 3.725$, $p < .001$, $d = 0.352$, suggesting that grades improved during the COVID-19 pandemic. However, we also found a significant increase in drug use from T1 to T2, $t(124) = 6.818$, $p < 0.001$, $d=0.61$ (see Figure 2.2B). Furthermore, the analysis revealed a significant reduction in social network size $t(124) = -5.568$, $p < 0.001$, $d=-0.50$ (Figure 2.2C) from before the pandemic to during the pandemic. Finally, we asked participants at T2 to retrospectively rate their well-being at T2, both pre-pandemic and during (one year into) the pandemic (see Figure 2.2D). Results revealed a significant decrease in well-being from before to during the pandemic, $t\ (124)= -6.14$, $p<0.001$, $d =-0.55$. The analysis did not reveal significant changes in subjective SES scores from Time 1 to

Time 2, $t(124) = 0.059$, $p = 0.953$. So far, the findings show that the COVID-19 pandemic affected different aspects of students' lives. Cumulative GPA improved during the pandemic, suggesting a possible boost in academic performance. However, this was accompanied by negative outcomes. Students reported increased drug use, smaller social networks, and lower well-being. Despite these changes, their perceived social status remained stable. In the next step, we used linear regression analyses to examine whether change scores (i.e., drug use, social network, subjective SES and wellbeing), significantly predicted a) change in GPA, b) GPA at T2, and c) change in drug use, controlling for age and gender.

(2a.) Predictors (change scores) of GPA change

In order to better understand whether changes in psychosocial outcomes are linked to the observed changes in GPA during the pandemic, we conducted a first regression analysis with cGPA change (from T1 to T2) as the dependent variable. The predictors included changes in drug use, social networks, subjective SES, and well-being. We found that none of the variables were associated with GPA change (p's > 0.2). Since change scores did not significantly predict GPA change, we next examined whether these same predictors - drug use, social networks, subjective SES, and well-being - were associated with GPA at T2. This allowed us to assess how these factors related to academic performance during the pandemic.

(2b.) Predictors (change scores) of GPA at T2

In the second regression analysis we explored whether change scores (i.e., change in drug use, social networks, subjective SES, as well as change in well-being) influenced GPA at T2. This analysis revealed that the change in drug use negatively predicted cumulative GPA at T2 ($ß = 0.011$, $p < 0.01$). None of the remaining change score variables significantly predicted cumulative GPA at T2 (p's> 0.32). The scatter plot in Figure 2.3 illustrates the negative relationship between changes in drug use and cumulative GPA at T2. As shown in the figure, a greater increase in drug use was associated with lower grades during the pandemic. Next, building on the findings from analysis 2b, where changes in drug use emerged as the only significant predictor of cumulative GPA at T2, we sought to better understand what might drive these changes in drug use during the pandemic. Since mental health problems are known to be predictive of and co-morbid with drug use (Czeisler et al., 2020; Swendsen et al., 2010), in the next regression analysis (2c), we explored whether pre-pandemic psychiatric diagnoses could help explain individual differences in increased drug use.

(2c.) Predictors of Drug use change

To better understand contributors of the increase in drug use during the pandemic, we assessed whether change in social networks, change in subjective SES, change in well-being, and pre-existing psychiatric diagnosis significantly predicted change in drug use. Results revealed that pre-existing psychiatric diagnosis positively predicted change in drug use ($ß = 7.65$, $p < 0.05$) (see Figure 2.4A), while change in social network was a marginally significant negative predictor of change in drug use ($ß= -0.78$, $p =0.056$) (see Figure 2.4B). None of the remaining variables significantly predicted change in drug use (p's> 0.38). Supplemental paired t-test analyses were conducted to assess change across each category of drug. The paired t-test analyses comparing drug use before and after the onset of the pandemic revealed that there were significant increases in the use of tobacco, alcohol, cannabis, cocaine, sedatives and hallucinogens, while there were no significant changes in the use of amphetamines, inhalants, opioids or other substances. See Supplemental Figure A.1 in Appendix A for box plots of the differences between drug use by drug type. For descriptive statistics by drug type see Supplemental Table A.1 in Appendix A. Descriptive statistics for the prevalence of psychiatric disorders are also provided in the Supplementary Appendix (see Supplemental Table A.2 of Appendix A). Overall, pre-pandemic psychiatric diagnoses were a significant predictor of increased substance use during the pandemic, suggesting that individuals with pre-existing mental health problems were more vulnerable to increased use of substances such as tobacco, alcohol and cannabis during the pandemic. Moreover, we also observed a marginally significant effect revealing that a greater reduction in social networks was associated with a smaller increase in drug use. This may suggest that decreased social interactions limited exposure to environments where substance use typically occurs. However, this finding should be interpreted with caution, given its statistical non-significance. Finally, to further explore potential contributors to students' academic performance during the pandemic, we conducted a cross-sectional analysis at T2. This analysis included a broader range of mental health symptoms and psychosocial factors, to assess how these variables, measured during the pandemic, were associated with cumulative GPA at the same time point. Unlike the earlier longitudinal analyses, this approach provides a snapshot of how various individual differences may have influenced academic outcomes during a particularly challenging period in time.

3) Cross-sectional analysis: T2 Predictors of GPA at T2

Hence, for the final analysis, a regression model with the undergraduate cumulative grade point average (cGPA) at T2 was conducted with the following predictors: general anxiety symptoms (BAI), general depressive symptoms (CESD), pre-existing psychiatric diagnosis, well-being change pre-pandemic relative to during pandemic, functional impairment related to pandemic (WSAS), social network total score (LSNS), drug use total score (ASSIST), objective SES (based on parent's average reported income), subjective SES, satisfaction with the university academic resources and classes during the pandemic, professor flexibility, COVID-19 related anxiety (CAS), and pandemic related stress (PSS), as well as age and gender as covariates. Results revealed a significant negative effect of drug use ($ß = -0.0094$, $p < .01$) (Figure 2.5A) and a significant positive effect of subjective SES ($ß = 0.091$, $p < .05$) (Figure 2.5B) on cGPA. Perceived stress was a marginally significant positive predictor of cGPA ($ß = 0.032$, $p =.051$), while none of the other variables significantly predicted cGPA (p's > .1). As shown in Figure 2.5A, a higher overall drug use was associated with worse GPAs, while Figure 2.5B reveals that a greater subjective SES was associated with higher GPAs. Overall, the findings suggest that the pandemic had varied impacts on students' mental health and academic performance. Social networks and well-being significantly declined, while drug use significantly increased following the onset of the pandemic. Despite these negative effects of the pandemic, there were mild increases in participants' GPAs. Drug use, predicted by pre-existing psychiatric conditions negatively impacted GPA, while higher subjective SES was associated with better GPA. This suggests that while the pandemic introduced numerous stressors and challenges, students who reported having higher socioeconomic status were more likely to succeed academically. At the same time, pre-pandemic psychiatric diagnoses predicted higher substance use, reinforcing the link between poor mental health and maladaptive coping skills.

Discussion

The purpose of this study was to better understand how the COVID-19 pandemic impacted mental health, psychosocial and academic outcomes in university students. Both longitudinal and cross-sectional analyses were used to examine changes over time and assess differences in students' academic, mental, and psychosocial functioning from before the pandemic (March 2019 to March 2020) to one year into the pandemic (March 2021 to April 2021). It should be noted that, given the university semester timeframes, GPAs corresponded to varying periods between Fall 2018 and Fall 2019 for Timepoint 1, while GPAs at Timepoint 2 reflected Fall 2020.

With regards to academic performance changes, in contrast to our original predictions, we found that students' GPAs increased during the pandemic (T2). This is in line with the literature showing mixed outcomes regarding the pandemic's impact on student achievement. While some studies report declines in academic performance (Borgaonkar et al., 2021; Haynes et al., 2024; Kuhfeld et al., 2022; Mahdy, 2020), others found stable or even improved grades during this period (Clark et al., 2021; LaGuardia Community College, Office of Institutional Research and Assessment, 2022; Vautier et al., 2023). Several factors may explain these inconsistencies, including variation in institutional grading policies (e.g., credit/no credit or leniency during remote learning), increased academic support or flexibility, and changes in assessment types (Holtzman et al., 2023; Vautier et al., 2023). Additionally, differences in sample characteristics, such as age, socioeconomic background, level of education, or field of study, may contribute to divergent findings across studies. Thus, while GPA increases may seem counterintuitive, they may reflect a complex interaction between academic demands, institutional policies, and psychological factors that unfolded differently across school contexts.

In order to understand potential contributors to the change in grades in our study, we examined whether changes in pandemic relevant psychosocial factors predicted the change in GPA. None of the predictors (longitudinal changes in drug use, social network size, SES and well-being) showed significant associations to the observed changes in GPA. This may indicate that the increase in GPA was driven by external factors not captured in our dataset, suggesting that the changes in GPA were independent of any measurable shifts in these variables. One possible explanation for the observed grade increase found in this study, may be greater grading leniency by professors during the pandemic. According to Vautier et al. (2023), professors and teaching assistants have reported that they were more flexible and lenient in their grading practices to accommodate challenges students faced during the pandemic. It has been documented that professors provided time extensions, pass/fail policies, assignment resubmissions and curving grades were reportedly allowed to mitigate disruptions caused by remote learning, personal hardships and mental health challenges during the pandemic (Vautier et al., 2023).

Interestingly, Vautier et al. (2023) showed that students' academic performance did not suffer during the pandemic, though they were less satisfied with their learning experience. The present study did not directly survey professors at Concordia University, however students were asked to rate their perception of their professor's flexibility. On the whole, a mean rating of professor flexibility was 55/100 on a visual analog scale ranging from 0-100, with moderate variance. This suggests that while students' perceptions of their professor flexibility were generally neutral, there was moderate in how different students viewed the degree of flexibility. Still, it should be noted that this variable is subject to bias since it reflects student perceptions, which may be influenced by individual interactions with professors or other contextual factors. Hence, although there was no significant relationship between student rated professor flexibility and GPA at T2 in our study, we cannot rule out the possible impact of professor leniency on grades during the pandemic. Obtaining a direct report from the professors would have provided a more accurate rating of their leniency in grading during the pandemic.

Although changes in the psychosocial factors mentioned above were not significantly associated with longitudinal changes in GPA, one of the variables, changes in drug use over the pandemic showed a significant negative relationship to academic performance during the pandemic (i.e. at T2). As shown in Figure 2.3 increases in substance use over the pandemic were associated with lower academic performance at T2. In particular, significant increases were seen in the use of tobacco, alcohol, cannabis, cocaine, sedatives and hallucinogens (see Supplemental Figure A.1). While prior research has shown that substance use increased during the pandemic, both in students and the general population (Charles et al., 2021; Sallie et al., 2020; White et al., 2020), this is, to our knowledge, the first study to show that increased drug use may have negatively impacted academic performance during the pandemic. Follow-up T2 (cross-sectional) analyses corroborate this pattern, with findings revealing that drug use at T2 significantly negatively predicted GPA during the pandemic (see Figure 2.5A), again implying that higher use of substances are associated with poorer academic outcomes.

Interestingly, despite the well-established links between poor mental health outcomes and academic functioning (Maghalian et al., 2023; Son et al., 2020; Unger, 2007), we did not find significant associations between mental health scales and GPA at T2. These included self-reported questionnaires assessing general symptoms of anxiety and depression (i.e., BAI, CESD), as well as measures that more specifically reflected pandemic related stressors (WSAS, CAS, PSS). These results held true even despite symptoms being expressed at clinically significant levels for a significant portion of the sample on the BAI and CESD, indicating that students showed a substantial degree of resilience during a challenging time. Moreover, even though general measures of anxiety and depressive symptoms were clinically elevated for the majority of the sample, most students did not endorse elevated levels of pandemic specific anxiety, stress and functional impairment (on the WSAS, CAS, and PSS), which may explain the non-significant associations between these measures and GPA at T2. Alternatively, it is possible that the observed increase in GPA at T2 does not reflect true academic gains, but rather grade inflation driven by contextual factors such as increased professor leniency during the pandemic. Thus, the absence of associations between GPA and mental health measures could be partly attributed to these confounding influences.

Nonetheless, while we did not find any associations between these mental health measures and academic performance, we noted that a significant portion of students in our sample reported being diagnosed with a psychiatric disorder prior to the pandemic (see Supplemental Table B.2). Given that mental health problems put individuals at risk for substance use (Czeisler et al., 2020; Swendsen et al., 2010; Volkow, 2020), we assessed the possible connection between mental health vulnerabilities and substance use during the pandemic. Our findings demonstrated that individuals with pre-existing psychiatric diagnoses exhibited increased substance use (see Figure 2.4A), aligning with our hypothesis that mental health vulnerabilities contributed to maladaptive coping and reduced academic performance. Indeed the literature supports this showing that mental health problems like anxiety and depression increase the risk of substance use disorders (Volkow, 2020), a trend exacerbated by the pandemic (Columb et al., 2020).

In summary, our findings reveal that while GPA increased during the pandemic, reports of mental well-being and social network sizes decreased, while substance use increased. Mental health indices did not significantly impact academic performance during the pandemic. However, greater substance use did negatively affect academic performance at T2. Moreover, pre-pandemic psychiatric diagnoses was associated with an increase in substance use during the pandemic, highlighting the well-established relationship between poor mental health and maladaptive coping skills. Taken together, these findings carry important implications. While overall student grades did not suffer following onset of the pandemic, either due to students adapting well to remote learning or for reasons of academic policy changes, a certain subset of students-namely those with pre-existing psychiatric conditions- did experience challenges with increased substance use, which in turn was associated with poorer academic performance. This may represent a potentially maladaptive coping mechanism that could have possible longer-term academic and functional consequences. Importantly, this highlights a need to implement proactive support for students at greater risk, including those with psychiatric histories during larger scale crises impacting the educational system.

Limitations and Future Directions

There are several limitations of this study that need to be acknowledged. First, the study's sample consisted of primarily female undergraduate university students majoring in psychology. Thus, the results may not generalize to the entire college student population. Future work could use a stratified nationwide sample across larger demographics and additional fields of study to address this limitation. Second, many of the measures in this study relied on self-report which is subject to biases.

Next, the within-subjects/repeated measures design used in this study has both limitations and strengths. Specifically, utilizing a within-subjects approach to assess participants GPA's has limitations when it comes to isolating the effects of the pandemic on academic outcomes, since student grades fluctuate as they progress through university for reasons unrelated to external events like the pandemic, including increases in course difficulty, adaptation to university, and other program-specific factors such as grading policies and assessment styles which can vary by major or year of university. Utilizing a between-subjects (cross-sectional) approach, like other studies (Kuhfeld et al., 2022; LaGuardia Community College, Office of Institutional Research and Assessment, 2022), which have compared test scores to same-grade/same year peers to limit threats to test score comparability pre- and post-pandemic may have been more appropriate in the assessment of grade change, because they offer a more direct comparison of cohorts unaffected by the pandemic to those impacted by the pandemic. Notably, previous studies examining the pandemic's impact on college educational attainment have often relied on subjective assessments rather than objective measures of academic performance. Use of objective GPA data (requesting students to obtain the information directly from their transcripts) was a strength of this study.

Future research may want to expand the academic variables, obtaining the results of standardized test outcomes to ensure generalizability of findings. Despite these limitations, this study provides valuable information about the impact of the COVID-19 pandemic on university students' mental well-being and how this relates to educational attainment.

Conclusion

In summary, the current findings illustrate the multifaceted impact of the COVID-19 pandemic on various aspects of students' lives. Social networks and reported well-being declined, while drug use significantly increased following the onset of the pandemic. Despite these negative consequences of the pandemic, students saw mild increases in their cumulative GPAs during the pandemic, which may be attributed to increased professor flexibility during this difficult time, though this hypothesis requires further verification. In addition, increased drug use negatively impacted GPA during the pandemic. The increased use of substances, in turn, was predicted by pre-existing psychiatric conditions. This suggests that those with diagnosed mental health problems were more likely to utilize maladaptive coping skills (via drug use in this case). This increased substance use in turn was associated with worsened academic performance during the pandemic. Overall, the results from this study suggest that a subgroup of students who are potentially most vulnerable during periods of crisis, -namely, those with pre-existing mental health conditions- are more prone to maladaptive coping strategies such as substance use. And given the observed link between substance use and poorer academic performance, it is possible that these individuals may be at higher risk for longer-term academic and functional consequences. This indicates that there is a need for targeted monitoring and early intervention in this more vulnerable population. As such, it may be important for universities to consider these findings when developing programs and promoting awareness of mental health services within the college setting.

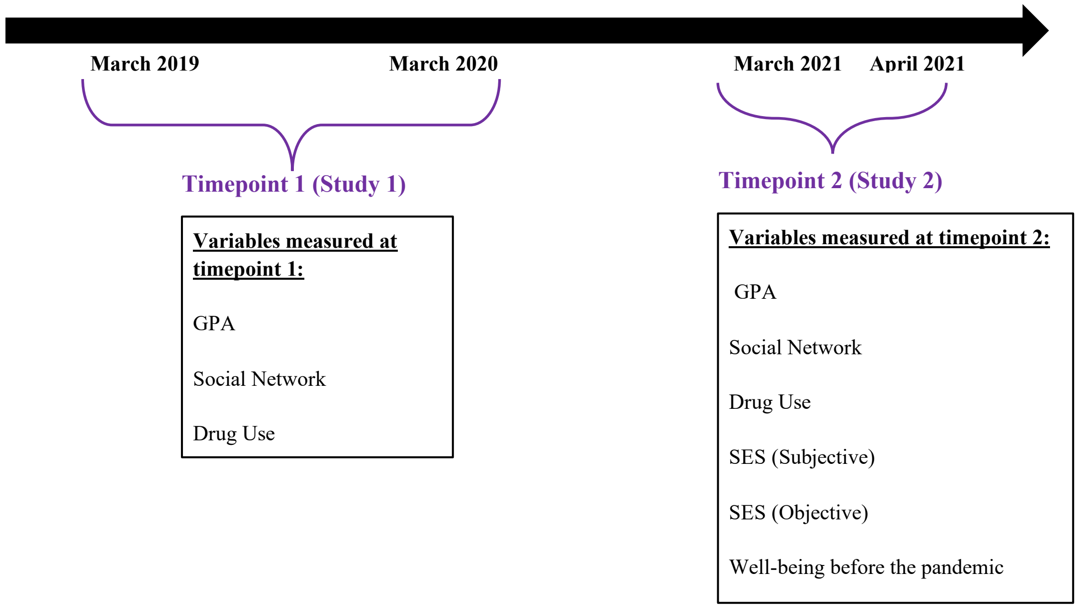
Table 2.1
Descriptive Statistics for Academic, Psychosocial, and Mental Health Variables Before and During the COVID-19 Pandemic

Variable	N	Range	Mean (SD)
Cumulative undergraduate GPA T1	115	1–4.3	3.24 (0.63)
Cumulative undergraduate GPA T2	122	1.8–4.3	3.39 (0.52)
Social Network T1	125	7–30	18.34 (4.95)
Social Network T2	125	2–28	16.30 (5.10)
Drug Use T1	125	0–38	7.38 (8.10)
Drug Use T2	125	0–95	16.53(18.56)
Socioeconomic Status (Parent's Income) T1	125	600–1901	1316 (455)
*Socioeconomic Status (Parent's Income) T2	97	50–950	337(341)
Subjective Social Status T1	125	2–10	6.18 (1.66)
Subjective Social Status T2	125	2–10	6.18 (1.59)
Center for Epidemiologic Studies Depression Scale (CES-D) score	125	1–52	23.35(11.62)
*Beck Anxiety Inventory (*BAI) score	125	0–59	18.61(15.04)
Well-being (Pre-pandemic)	125	5–100	71.1(20.37)

Well-being (During Pandemic)	125	0–100	56.85(23.14)
Work and Social Adjustment Scale (WSAS) score	125	0–38	18.33(8.40)
Corona Virus Anxiety Scale (CAS) score	125	0–16	2.19(3.42)
Perceived Stress Scale (PSS-10-C) score	125	9–39	20.93(4.11)

*Note. The table d*isplays the means, standard deviations, and ranges for key variables assessed before (T1) and during (T2) the COVID-19 pandemic. Measures include academic performance (cumulative GPA), social network size, drug use scores, socioeconomic status (both objective and subjective), mental health indicators (depression and anxiety), overall well-being, functional impairment, and pandemic-related stress and anxiety.*Of note, SES at timepoint 2 was assessed on different scale from timepoint 1, therefore the two scores are not directly comparable.

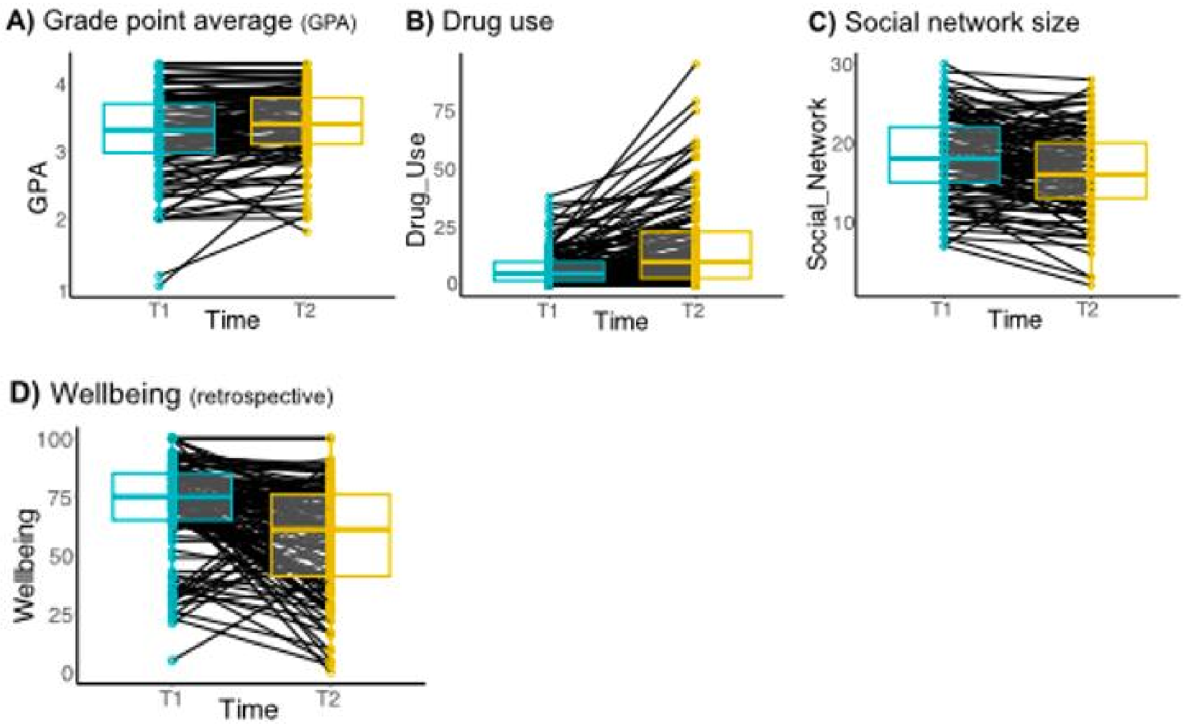
Figure 2.1
Study Procedure (Timeline)



Note: Schematic Figure showing the sequence of assessments conducted at two timepoints in the longitudinal study examining the impact of the COVID-19 pandemic on university students. Data acquisition at timepoint 1 (pre-pandemic) included measures of academic performance (Grade Point Average; GPA), social network size (Luben Social Network Scale), drug use (Alcohol, Smoking and Substance Involvement Screening Test; ASSIST), subjective socioeconomic status (MacArthur Scale), objective socioeconomic status (parental income), and self-reported psychiatric diagnosis. These variables (except for psychiatric diagnosis) were reassessed at timepoint 2 (during the pandemic). In addition we acquired additional cross-sectional measures including: well-being, anxiety symptoms (Beck Anxiety Inventory; BAI), depressive symptoms (Center for Epidemiologic Studies Depression Scale; CES-D), functional impairment related to the pandemic (Work and Social Adjustment Scale; WSAS), COVID-19-related anxiety (Coronavirus Anxiety Scale; CAS), pandemic-related stress (Perceived Stress Scale; PSS).

Figure 2.2

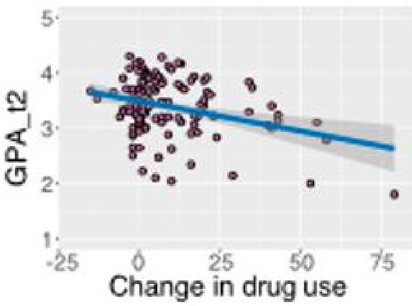
Changes in GPA, Drug Use, Social Network Size, and Well-being Before and During the pandemic



Note. Within-subject changes in (A) Grade Point Average (GPA), (B) drug use (Alcohol, Smoking and Substance Involvement Screening Test; ASSIST), (C) social network size (Luben Social Network Scale), and (D) perceived well-being from Timepoint 1 (pre-pandemic; T1) to Timepoint 2 (during the pandemic; T2). Each line represents an individual participant's change score from T1 to T2. Boxplots summarize the distribution at each timepoint, with lower and upper hinges corresponding to the 25th and 75th percentiles, and the central line representing the median. Paired-sample t-tests revealed a significant increase in GPA and drug use, along with significant decreases in social network size and perceived well-being.

Figure 2.3

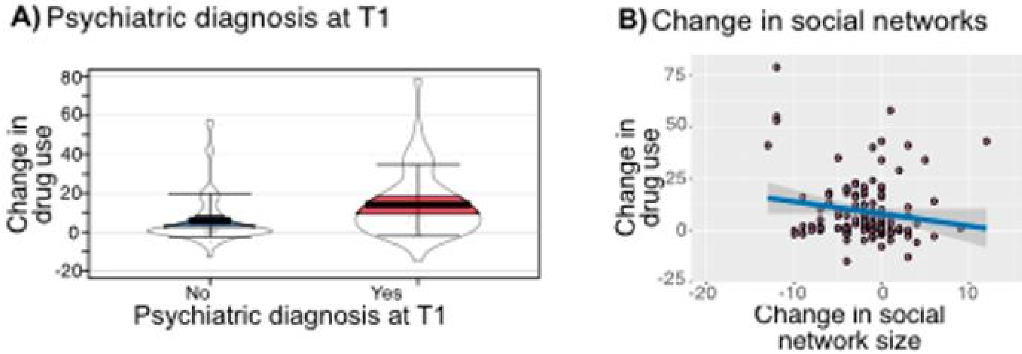
Change in drug use predicts GPA at time 2



*Note. (*A.) The scatterplot displays the negative relationship between changes in substance use (ASSIST total score) from pre-pandemic (T1) to during the pandemic (T2) and academic performance (Grade Point Average; GPA) at T2. The shaded area around the regression line represents the 95% confidence interval.

Figure 2.4

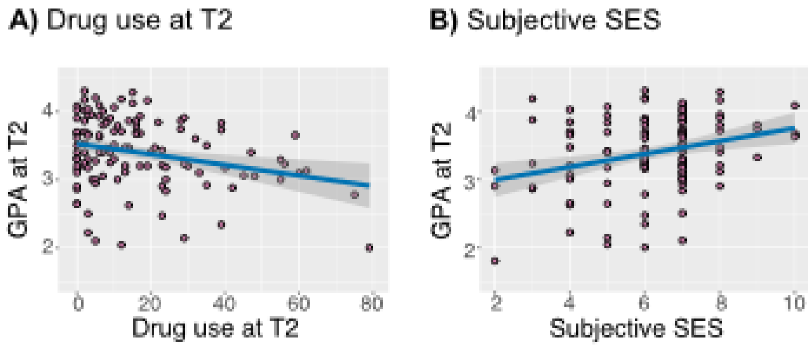
Factors predicting change in drug use



Note. (A) Violin plot showing the distribution of change in drug use scores from Timepoint 1 (pre-pandemic) to Timepoint 2 (during the pandemic), separated by presence or absence of a pre-pandemic psychiatric diagnosis. The width of each violin reflects the density of observations at each value, with an overlaid boxplot displaying the median (thicker horizontal line within the violin), interquartile range, and potential outliers. (B) Scatterplot depicting the negative relationship between change in social network size and change in drug use scores. The shaded region represents the 95% confidence interval of the regression line.

Figure 2.5

T2 variables predicting GPA at T2



Note: Scatterplots illustrating the significant predictors of cumulative Grade Point Average (GPA) at Timepoint 2 (T2). (A) Drug use at T2, negatively predicted GPA. (B) Subjective socioeconomic status (SES positively predicted GPA. Shaded regions around regression lines represent 95% confidence intervals.

CHAPTER FOUR:

GENERAL DISCUSSION

The overall aim of this dissertation is to provide a comprehensive understanding of the factors that influence and predict educational attainment. The first manuscript explores the role of cognitive abilities, learning strategies and motivational factors in determining academic performance at the collegiate level. The second manuscript extended this work by exploring the impact of the COVID-19 pandemic on students' academic outcomes and psychosocial functioning, using a longitudinal design. Together, the studies provide a comprehensive overview and understanding of both individual-level factors (such as cognitive abilities or the willingness to exert mental effort) and broader contextual stressors (such pandemic related disruptions) that affect academic performance at the post-secondary level. In this final chapter of the dissertation, I first discuss the individual contributions of the two studies to the literature on educational attainment. I then try to synthesize the findings from both studies, considering their broader implications for optimizing educational policies and interventions.

STUDY 1: COGNITIVE AND MOTIVATIONAL PREDICTORS OF EDUCATIONAL ATTAINMENT

The goal of the first study in this dissertation was to investigate the role that cognitive abilities (including fluid intelligence, attention, and processing speed), goal-directed learning strategies and motivational factors play in predicting academic success in university students. Results revealed that engagement in model-based learning i.e., a cognitively taxing yet efficient goal-directed learning strategy (Bolenz et al., 2019; Eppinger et al., 2013; Otto et al., 2015), and the need for cognition (NFC) i.e., the willingness to engage in mentally demanding activities (Cacioppo et al., 1996; Cacioppo & Petty, 1982), positively predicted academic performance (as measured by an aggregate of high school average grades and university grade point average). Although none of the other cognitive variables were significantly associated with educational attainment, subsequent analyses revealed that some of these variables individually predicted use of the model-based learning strategy, and NFC engagement. Specifically, increased fluid intelligence and attention predicted model-based learning, while fluid intelligence predicted NFC. Additionally, NFC was negatively predicted by reward sensitivity, an indicator of the willingness to expand cognitive effort**.** These findings suggest that both the ability to engage in higher-order (goal-directed) learning strategies and motivational factors, such as the willingness to expend cognitive effort play important roles in determining academic success.

The results of this study align with prior work showing that a stronger need for cognition is associated with better cognitive performance (Cacioppo et al., 1996; Fleischhauer et al., 2010), and academic outcomes (Hawthorne et al., 2021; Liu & Nesbit, 2024). Additionally, the current study shows for the first time that increased use of the model-based learning strategy predicts greater academic performance. Conversely, our findings diverge from studies that demonstrate a direct relationship between cognitive abilities and educational attainment (Dubuc et al., 2022; Zisman & Ganzach, 2022). One interpretation of these findings could be that basic cognitive functions, such as attention and processing speed, along with core cognitive capacities like fluid intelligence, may support the development and application of “higher-level” learning strategies, which in turn indirectly affect academic success. Additionally, it is possible that there are mediating or moderating factors at play, which may alter or buffer the direct relationship between cognitive ability and academic performance. Indeed, work by Shi and Qu (2021, 2022b) reveals that the effect of cognitive ability on academic achievement may be mediated by self-discipline and personality characteristics, and moderated by planning and psychological health. This highlights the importance of motivational and self-regulatory mechanisms in translating cognitive potential into academic success.

All in all, the findings of this study suggest that academic success is not solely a function of raw cognitive ability but is also dependent upon students’ willingness to engage in cognitively effortful tasks, and capacity for implementing goal-directed learning strategies. These results emphasize the potential value of educational interventions that cultivate and encourage the use of deliberate, strategic learning techniques, particularly in environments that reward flexible problem-solving. The Need for Cognition (NFC) is considered to be a generally stable trait-like disposition (Cacioppo & Petty, 1982), with some potential malleability in younger individuals (Bruinsma & Crutzen, 2018; Lavrijsen et al., 2024). As such, it may be possible to design academic environments that stimulate curiosity, promote deep learning, and reinforce the value of cognitive effort, thereby supporting behaviors aligned with high NFC. All together, these findings highlight the importance of supporting both motivational engagement and goal-directed learning processes as important drivers of educational attainment, potentially complementing the role of cognitive abilities commonly assessed in educational research

STUDY 2: IMPACT OF THE COVID-19 PANDEMIC ON EDUCATIONAL ATTAINMENT AND MENTAL HEALTH

The second study in this dissertation employs a longitudinal design to examine how contextual disruptions, such as the COVID-19 pandemic, affect mental health and psychosocial functioning in university students. Specifically, it explores how changes in these domains influence academic performance.

While prior research has documented declines in academic performance due to the pandemic **(**Borgaonkar et al., 2021; Fahle et al., 2023; Haynes et al., 2024; Mahdy, 2020**)**, there is limited data on how changes in psychosocial and mental health outcomes potentially contribute to these outcomes. Importantly, there is a paucity of longitudinal research examining the impact of the pandemic on university student outcomes. Most studies to date have relied on cross-sectional designs and subjective perceptions of academic performance (Ferrer et al., 2023; Reyes-Portillo et al., 2022), with few incorporating pre-pandemic baseline data or objective markers of academic performance (including reports of official GPA or standardized test results). To address these gaps, the current study utilized both longitudinal data-collected before and during the pandemic-and cross-sectional data to examine how pandemic-related disruptions influenced students' academic performance, mental health, and psychosocial functioning. This combined approach allows for both the examination of changes over time and a broader understanding of how the pandemic may have influenced academic, psychological, and social outcomes.

The current study reveals several key findings regarding the impact of the pandemic on student outcomes. While students' GPAs increased during the pandemic, they also reported significant declines in mental well-being and social networks, along with increased substance use. Despite negative psychosocial outcomes, this mild improvement in academic performance suggests that other factors, like more lenient grading policies adopted by universities, may have played a role, however this explanation remains untested. Additionally, cross-sectional findings reveal: higher levels of substance use were associated with lower GPAs during the pandemic. Notably, increases in substance use were predicted by pre-existing psychiatric conditions, indicating that students with prior mental health diagnoses were more likely to engage in maladaptive coping strategies.

Previous studies corroborate several findings from this study, including increased substance use in college students during the pandemic (Charles et al., 2021), as well as reports of reduced mental well-being (Hu et al., 2022; Li et al., 2020; Reyes-Portillo et al., 2022), and smaller social networks or connections (David et al., 2022; Jeffers et al., 2022; Lowe et al., 2023b). Moreover, it has been well-documented that psychiatric conditions, such as anxiety and depressive disorders, frequently co-occur with substance use problems or substance misuse (Volkow et al., 2020). In line with this, our study demonstrated that having a pre-existing psychiatric disorder was associated with increased substance use during the pandemic. Additionally, to our knowledge, this is the first study to show that increased substance use, potentially as a form of maladaptive coping, was linked to poorer academic performance among university students during this period. These results emphasize a need for early identification and support for students with mental health challenges, particularly during times of widespread disruption. Ideally, implementing preventative mental health interventions and substance use monitoring on university campuses may help mitigate the academic consequences of maladaptive coping strategies in at-risk students.

At the same time, not all findings aligned with prior research. While several studies have reported declines in academic performance or some form of academic disruption during the pandemic (Borgaonkar et al., 2021; Fahle et al., 2023; Haynes et al., 2024, Hu et al., 2022; Mahdy, 2020), the present findings show a modest improvement in GPA among university students. This discrepancy may reflect variability in study design, sample characteristics, academic disciplines, or institutional grading policies during the pandemic (Karadag, 2021; Vautier et al., 2023). Future research should continue monitoring student outcomes over time to assess the longer-term educational impact of the pandemic. In particular, tracking trends in academic performance, retention and acceptance rates, time to degree completion, and the use of interventions used to remedy adverse changes associated with pandemic-related disruptions may yield valuable insights. Such knowledge may be important for informing proactive strategies to mitigate the academic and psychological consequences of future large-scale disruptions affecting the student population.

MULTIFACETED INFLUENCES ON ACADEMIC ATTAINMENT: COGNITIVE, MOTIVATIONAL, AND CONTEXTUAL CONTRIBUTIONS

This dissertation aimed to examine the various factors that shape academic performance. Although the two studies focused on different domains, Study 1 on cognitive and motivational traits, and Study 2 on impact of external stressors in the context of a worldwide pandemic, they collectively highlight that educational attainment is shaped by a variety of influences, including but not limited to cognitive ability, strategic learning engagement, intrinsic motivation, and maladaptive coping in the context of a major external disruption (i.e., the COVID-19 pandemic). See Figure B.1 in Appendix B for a visual summary of the conceptual framework linking cognitive abilities, motivational traits, learning strategies, and external disruptions to academic performance.

Study 1 found that students who engaged in goal-directed, model-based learning strategies and who reported a stronger need for cognition (i.e., the tendency to enjoy and seek out cognitively demanding tasks) tended to perform better academically. Interestingly, while core cognitive ability (i.e., fluid intelligence) did not directly predict academic outcomes, it was associated with both model-based learning and NFC. Evidently then, foundational cognitive skills play a role in supporting the use of advanced learning strategies and intrinsic motivation to engage in cognitively demanding tasks, whilst such learning strategies and motivation towards cognitive engagement are important for academic success. It is possible that core cognitive ability may essentially serve to lay the groundwork for more complex thinking strategies, which then feed into academic success.

While model-based learning strategies defined in the computational reinforcement learning framework (Daw et al., 2011; Drummond & Niv, 2020; Kool et al., 2017) have not yet been widely investigated in relation to educational attainment, prior work has established that executive functions-which are positively associated with model-based learning- are critical for academic performance (e.g., working memory, cognitive flexibility, and inhibitory control). Given that model-based decision-making is positively associated with executive functioning (Eppinger et al., 2013; Otto et al., 2015), it is possible that executive skills facilitate the use of model-based learning strategies in academic contexts. In other words this may be one mechanism by which model-based learning is related to academic success. Interestingly, it was the general tendency to engage in model-based learning, regardless of reward contingencies, that was positively associated with academic performance. In contrast, meta-control of model-based learning (i.e., selectively increasing goal-directed strategy use only when rewards were high) was not associated with better academic outcomes. This suggests that stable, intrinsic tendencies toward goal-directed thinking, rather than context-dependent strategic adjustments based on incentives, may be more strongly linked to academic success. Supporting this view, we also found that Need for Cognition (NFC) was negatively associated with reward sensitivity in an incentivized task-switching paradigm. Specifically, individuals high in NFC were more willing to exert cognitive effort even when average reward rates were low, indicating that their engagement in cognitively demanding tasks was less influenced by external incentives. These findings align with prior work (Sandra & Otto, 2018) and suggest that individuals with high NFC are more intrinsically motivated to pursue effortful thinking, which may support sustained academic engagement over time. Indeed, NFC itself has been hypothesized to contribute to academic success via multiple pathways, including greater intrinsic motivation to pursue cognitively demanding tasks (Kramer et al., 2021; Sandra & Otto, 2018) and an overall preference for more difficult mental tasks to easier ones (Cacioppo & Petty, 1982), better problem solving skills and general intelligence (Hill et al., 2013), as well as academic self-concept and interest (Keller et al., 2019; Luong et al., 2017).

In addition to individual differences in cognitive and motivational factors, external stressors also play an important role in shaping student success, and should be considered to gain a more comprehensive understanding of the correlates of educational attainment (Cao et al., 2024; Fahle et al., 2023; Hu et al., 2022; Izumi et al., 2021; Reyes-Portillo et al., 2022). Study 2 illustrated how life stressors, in the context of a global pandemic impacted student outcomes, highlighting the importance of considering contextual influences, and potentially risk factors, when studying models of academic success. While average GPA appeared to improve during the pandemic, potentially due to lenient grading policies (Holtzman et al., 2023; Vautier et al., 2023), this apparent improvement may obscure underlying challenges faced by more vulnerable students. The finding that pre-existing psychiatric diagnoses (i.e., psychiatric diagnoses diagnosed prior to the pandemic) was associated with increased substance use during the pandemic reveals an obvious but important point: that students with existing mental health challenges are more likely to consume drugs and alcohol, potentially as a coping tool in response to increased stress. Negative consequences of excessive substance use are well-established

(Arria et al., 2015; Czeisler et al., 2020; Swendsen et al., 2010; Vo et al., 2022; Welsh et al., 2019). Indeed, increased substance in this study was associated with poorer academic performance, just one example of the deleterious effects of increased substance use. These results highlight the importance of providing monitoring and targeted interventions for at-risk students, including those with established mental health difficulties during external disruptions, such as in the case of a global pandemic. More broadly, discussions surrounding intervention strategies in the context of the pandemic have focused on helping students process their pandemic experience, manage uncertainty and change, and re-establish social and community connections (Cipolletta et al., 2024; National Academies of Sciences, Engineering, and Medicine, 2023). These intervention targets are particularly relevant given evidence that the pandemic not only exacerbated pre-existing mental health concerns among college students but also gave rise to new mental health struggles due to difficulty adapting to the challenges brought on by the pandemic (David et al., 2022). Specifically, David et al. (2022) found that increased loneliness related to reduced social activities, interactions and quarantine, and difficulties meeting academic demands remotely in home environments, contributed to declines in student mental health. Building on these findings, the present study highlights an additional and more specific need, that is, integrating substance use interventions and awareness campaigns as well as promoting the development of healthier coping strategies among students. In this post-pandemic era, virtual interventions may be particularly effective in supporting student mental health, given their accessibility, flexibility, and potential to reach large and diverse student populations (Rutkowska, 2022). For example, one study showed that participation in an online multi-component intervention program combining evidence-based strategies from cognitive-behavioral therapy, positive psychology, mindfulness, and lifestyle medicine, helped improve university students' psychological well-being, and was linked to reduced symptoms of psychological distress, anxiety, and alcohol use (Theurel et al., 2022). Importantly, when thoughtfully designed, such remote interventions may also help mitigate social isolation by incorporating opportunities for virtual peer interaction and community-building.

All in all, academic success is not solely determined by a student's cognitive or motivational profile, it is also shaped by their ability to manage external pressures and maintain emotional well-being. These results emphasize the need for academic interventions that target both cognitive and motivational development, while also offering support for students who may be more susceptible to stress and mental health challenges, particularly during periods of widespread disruption.

LIMITATIONS, STRENGTHS AND FUTURE DIRECTIONS

Limitations

There are several limitations to consider when interpreting the results of the studies presented in this dissertation. First, the samples were relatively homogeneous, consisting primarily of undergraduate psychology students, with limited demographic diversity (i.e., predominantly Caucasian and female), which may limit the generalizability of the findings. Second, both studies relied heavily on self-reported data, including academic performance (e.g., GPA and high school grades), psychological traits (e.g., Need for Cognition), and psychosocial, mental health and substance use measures, all of which may be subject to recall inaccuracies and social desirability bias. Notably, in the first study, academic performance was based solely on participants' recollection, whereas the second study instructed students to retrieve their official records representing an improvement over the approach of the first study, though still reliant on self-report. Ideally, future studies should obtain direct access to institutional academic transcripts to enhance measurement validity. Furthermore, the sample included students across varying academic years, course loads, and enrollment statuses (e.g., part-time vs. full-time), which were not controlled for in the analyses. Future research should account for these variables to better isolate the effects of the predictors on academic attainment.

Strengths

Despite these limitations, the studies in this dissertation have several strengths. First, both cross-sectional and longitudinal data methods were used to capture and explore individual-level predictors of educational attainment and to assess the impact of external stressors, namely, those related to the COVID-19 pandemic on student outcomes over time. In addition, the studies employed a range of validated measurement approaches, including standardized assessments of cognitive abilities, self-report questionnaires to assess mental health symptoms, substance use, and pandemic-related stressors, as well as computational modeling techniques to evaluate learning strategies. These different methods allowed for a more nuanced and mechanistic understanding of how such factors contributed to academic outcomes.

Directions for Future Research

Although the present dissertation offers a broad exploration of academic attainment, it does not account for all potentially relevant cognitive influences. In particular, the first study was limited in scope with respect to the range of cognitive measures included. For instance, it did not assess verbal abilities, memory functions, or working memory capacity, which are domains that have been shown to play an important role in university academic achievement (Baldwin, 2020; Berkowitz & Stern, 2018; Süß et al., 2002). Future research would benefit from incorporating a more comprehensive set of cognitive predictors to examine their unique and combined contributions to academic performance in higher education.

Another promising direction involves examining how the NFC (considered an intrinsic motivation or tendency towards engaging in and enjoy effortful cognitive activity), might be actively cultivated in university students. While NFC has been widely studied as a trait-like predictor of academic success (Grass et al., 2017; Hawthorne et al., 2021; Neigel et al., 2017), less is known about how it can be intentionally fostered in postsecondary contexts. Recent work by Aerts et al. (2024) proposed strategies to foster NFC in children and adolescents, rooted in a developmental framework (Matthews, 2018). Some of these strategies included implementing and creating an optimally challenging learning environment, enhancing appraisals of cognitive effort, and modeling cognitive engagement. Although these strategies have primarily been studied in childhood and adolescence, their application for promoting cognitive engagement in higher education warrants further investigation. For instance, future research should examine whether interventions incorporating these aforementioned strategies can effectively promote NFC among college students and, in turn, support academic motivation and achievement.

Next, although we studied motivational factors and mental health in the context of educational attainment in two separate studies, future work would benefit from examining how these constructs interact. For instance, while motivation is a known predictor of academic performance (Cacioppo et al., 1996; Meier et al., 2014; Richardson et al., 2009; Robinson, 2004; Walberg et al.,1986), its effects may be contingent on students' psychological well-being, given the importance of mental health in academic settings (Shi & Qu, 2021). Future research could explore whether mental health mediates the relationship between motivation and academic outcomes. Incorporating objective indicators, such as pupil dilation (a known marker of mental effort) (van der Wel et al., 2018) and biofeedback tools like heart rate variability, skin conductance, and respiration (which reflect stress-related arousal) (Chan et al., 2012) may provide a more objective and nuanced understanding of how students engage cognitively and emotionally in academic contexts (Hickey et al., 2021).

Finally, future research is needed to study the long-term consequences of the pandemic on student education and academic outcomes. This dissertation focused on how external stressors related to the COVID pandemic, influenced student outcomes. Although we identified several negative changes in psychosocial and mental health related outcomes, students' academic performance did not appear to suffer. However, it remains unclear whether this apparent stability reflects true academic resilience or is partly attributable to factors such as more lenient grading policies, modified course structures, or relaxed academic expectations that were implemented during the pandemic (Holtzman et al., 2023; Vautier et al., 2023). Future studies should explore the potential downstream effects of these temporary accommodations, particularly whether students during the pandemic-period experience challenges in subsequent academic or professional settings. Follow-up and longitudinal studies that track students are especially needed to assess the lasting impacts of the pandemic on achievement, preparedness, and broader indicators of success (for example vocational/employment opportunities and more).

IMPLICATIONS AND CONCLUSION

All in all, this dissertation attempts to examine the factors that contribute to educational attainment by considering foundational cognitive abilities, strategic learning, motivational constructs, as well as external disruptions in the context of a global pandemic. This, in effect, aims to provide a more comprehensive framework for understanding educational attainment. While cognitive aptitude has historically been the primary focus of previous studies (Deary et al., 2007; Morosanova et al., 2022) the present work also considers the roles of non-cognitive influences including motivation and strategic learning engagement in predicting academic performance, finding that both NFC and goal-directed (model-based) learning individually predict academic outcomes. Moreover, we were able to examine the influence of external stressors and change secondary to the COVID-19 pandemic, on academic achievement, highlighting that individuals with pre-existing mental health conditions were more susceptible to increased substance use in response to the pandemic, and this increased substance was associated with poorer academic outcomes. By examining such links this dissertation offers a multifaceted perspective into the mechanisms underlying academic success, thereby informing educational policy, practice and supportive academic interventions. For instance, programs aimed at fostering students' motivation (specifically, NFC) and promoting goal-directed learning approaches, and addressing mental health challenges, may yield substantial benefits in improving educational outcomes. Notably, pandemic related findings imply that there is a need for targeted interventions to support students during periods of disruption. In particular, screening for and addressing mental health challenges and substance use, may help mitigate the academic struggles associated with external stressors. Targeting and monitoring students with pre-existing psychological disorders in the context of a global disruption is key.

In conclusion, findings reported in this dissertation emphasize the value of adopting a broad, multi-method approach to examining the determinants of academic performance at the college level. By integrating self-report questionnaires with experimental paradigms and computational analyses, this research offers a more nuanced understanding of both the observable behaviors and the underlying cognitive and motivational mechanisms that contribute to academic success. A collective focus on cognitive abilities, motivational traits, learning strategies, and contextual influences allows for a more comprehensive view of student academic functioning. Moreover, these results have practical implications for the design of academic interventions. Importantly, such interventions should account for contextual variables and provide support systems that not only foster cognitive and motivational skills, but also equip students with strategies to navigate and adapt to external stressors.

References

Abdelrahman, R. M. (2020). Metacognitive awareness and academic motivation and their impact on academic achievement of Ajman University students. *Heliyon*, *6*(9), e04192. https://doi.org/10.1016/j.heliyon.2020.e04192

Adler, N. E., Epel, E., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary results from the MacArthur Studies of Subjective Social Status. *Health Psychology, 19* (6), 586–592. https://doi.org/10.1037/0278-6133.19.6.586

Advokat, C., Martino, L., Hill, B. D., & Gouvier, W. (2007). Continuous Performance Test (CPT) of college students with ADHD, psychiatric disorders, cognitive deficits, or no diagnosis. *Journal of Attention Disorders, 10*(3), 253–256. https://doi.org/10.1177/1087054706292106

Aerts, E., Lavrijsen, J., Preckel, F., & Verschueren, K. (2024). A Theoretical Framework for the Development of Need for Cognition in Childhood and Adolescence. *Journal of Intelligence*, *12*(10), 99. https://doi.org/10.3390/jintelligence12100099

Ahn, M. H., Lee, J., Suh, S., Lee, S., Kim, H. J., Shin, Y. W., & Chung, S. (2020). Application of the Stress and Anxiety to Viral Epidemics-6 (SAVE-6) and Coronavirus Anxiety Scale (CAS) to Measure Anxiety in Cancer Patient in Response to COVID-19. *Frontiers in psychology*, *11*, 604441. https://doi.org/10.3389/fpsyg.2020.604441

Aristovnik, A., Keržič, D., Ravšelj, D., Tomaževič, N., & Umek, L. (2020). Impacts of the COVID-19 pandemic on life of higher education students: A global perspective. *Sustainability, 12*(20), 8438. https://doi.org/10.3390/su12208438

Arria, A. M., Caldeira, K. M., Bugbee, B. A., Vincent, K. B., & O'Grady, K. E. (2015). The academic consequences of marijuana use during college. *Psychology of addictive behaviors : journal of the Society of Psychologists in Addictive Behaviors*, *29*(3), 564–575. https://doi.org/10.1037/adb0000108

Arum, R., & Roksa, J. (2011). *Academically adrift: Limited learning on college campuses*. University of Chicago Press.

Aucejo, E. M., French, J., Ugalde Araya, M. P., & Zafar, B. (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *Journal of Public Economics*, *191*, 104271. DOI: 10.1016/j.jpubeco.2020.104271

Auerbach, R. P., Alonso, J., Axinn, W. G., Cuijpers, P., Ebert, D. D., Green, J. G., Hwang, I., Kessler, R. C., Liu, H., Mortier, P., Nock, M. K., Pinder-Amaker, S., Sampson, N. A., Aguilar-Gaxiola, S., Al-Hamzawi, A., Andrade, L. H., Benjet, C., Caldas-de-Almeida, J.

M., Demyttenaere, K., Florescu, S., … Bruffaerts, R. (2016). Mental disorders among college students in the World Health Organization World Mental Health Surveys. *Psychological medicine*, *46*(14), 2955–2970. https://doi.org/10.1017/S0033291716001665

Baars, M. A., Nije Bijvank, M., Tonnaer, G. H., & Jolles, J. (2015). Self-report measures of executive functioning are a determinant of academic performance in first-year students at a university of applied sciences. *Frontiers in psychology*, *6*, 1131. https://doi.org/10.3389/fpsyg.2015.01131

Bacon, D. R., & Bean, B. (2006). GPA in research studies: An invaluable but neglected opportunity. *Journal of Marketing Education, 28*(1), 35–42.

Baldwin, A. (2020). *College success* (Section 6.1: Memory). OpenStax. https://openstax.org/books/college-success/pages/6-1-memory

Banerjee, D., & Rai, M. (2020). Social isolation in COVID-19: The impact of loneliness. *International Journal of Social Psychiatry, 66*(6), 525–527. https://doi.org/10.1177/0020764020922269

Baum, S., Kurose, C., & Ma, J. (2013). *How College Shapes Lives: Understanding the Issues*. New York: College Board.

Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: psychometric properties. *Journal of consulting and clinical psychology*, *56*(6), 893–897. https://doi.org/10.1037//0022-006x.56.6.893

Becker, S. P., Breaux, R., Cusick, C. N., Dvorsky, M. R., Marsh, N. P., Sciberras, E., & Langberg, J. M. (2020). Remote Learning During COVID-19: Examining School Practices, Service Continuation, and Difficulties for Adolescents With and Without Attention-Deficit/Hyperactivity Disorder. *The Journal of adolescent health : official publication of the Society for Adolescent Medicine*, *67*(6), 769–777. https://doi.org/10.1016/j.jadohealth.2020.09.002

Bekerman, U., & Rondanini, A. (2020). El Acceso a internet como garantía del derecho a la educacio ́n. *Diario DPI Suplemento Salud, 58*, 1–7. https://doi.org/10.2139/ ssrn.3576719

Berkowitz, M., & Stern, E. (2018). Which Cognitive Abilities Make the Difference? Predicting Academic Achievements in Advanced STEM Studies. *Journal of Intelligence, 6*(4), 48. https://doi.org/10.3390/jintelligence6040048

Best, J. R., & Miller, P. H. (2010). A developmental perspective on executive function. Child *Development, 81,* 1641–1660. https://doi. org/10.1111/j.1467-8624.2010.01499.x

Bhagavathula, A. S., & Khubchandani, J. (2023). Persistent Black-White disparities in mental healthcare needs during the COVID-19 pandemic: A call for action. *The International journal of social psychiatry*, *69*(5), 1293–1295. https://doi.org/10.1177/00207640221143292

Bjorklund-Young, A. (2016). *What do we know about developing students' non-cognitive skills?* Institute for Education Policy, Johns Hopkins School of Education.

Bolenz, F., Kool, W., Reiter, A. M., & Eppinger, B. (2019). Metacontrol of decision-making strategies in human aging. *eLife*, *8*, e49154. https://doi.org/10.7554/eLife.49154

Bolenz, F., Profitt, M. F., Stechbarth, F., Eppinger, B., & Strobel, A. (2022). Need for cognition does not account for individual differences in metacontrol of decision making. *Scientific reports*, *12*(1), 8240. https://doi.org/10.1038/s41598-022-12341-y

Borgaonkar, A. D., Sodhi, J., Vijayabalan, R., & Nair, A. S. K. A. (2021, July). *A comparative study of the impact of COVID-19 pandemic on student participation and performance in first-year engineering courses* [Paper presentation]. 2021 ASEE Virtual Annual Conference Content Access, Virtual Conference. https://doi.org/10.18260/1-2–36566

Bors, D. A., & Stokes, T. L. (1998). Raven's Advanced Progressive Matrices: Norms for first-year university students and the development of a short form. *Educational and Psychological Measurement, 58*(3), 382–398. https://doi.org/10.1177/0013164498058003002

Brouwers, S.A., Van de Vijver, F.J.R., & Van Hemert, D.A. (2009). Variation in Raven's Progressive Matrices scores across time and place. *Learn. Individ. Differ*. *19*, 330–338.

Bruinsma, J., & Crutzen, R. (2018). A longitudinal study on the stability of the need for cognition. *Personality and Individual Differences, 127*, 151–161. https://doi.org/10.1016/j.paid.2018.02.001

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology, 42*(1), 116–131. https://doi.org/10.1037/0022-3514.42.1.116

Cacioppo, J. T, Petty, R. E., & Kao, C. F. (1984). The efficient assessment of need for cognition. *Journal of Personality Assessment, 48*, 306-307.

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin, 119*(2), 197–253. https://doi-org.ezproxy.lsus.edu/10.1037/0033-2909.119.2.197

Campo-Arias, A., Pedrozo-Cortés, M. J., & Pedrozo-Pupo, J. C. (2020). Pandemic-related perceived stress scale of COVID-19: An exploration of online psychometric performance. *Revista Colombiana de Psiquiatría, 49*(4), 229–230. https://doi.org/10.1016/j.rcp.2020.05.005

Cao, W., Fang, Z., Hou, G., Han, M., Xu, X., Dong, J., & Zheng, J. (2020). The psychological impact of the COVID-19 epidemic on college students in China. *Psychiatry Research*, *287*, 112934. DOI: 10.1016/j.psychres.2020.112934

Cao, W., Gnana Sanga Mithra, S., & B R, A. (2024). Unraveling the factors shaping academic success: A structural equation modeling approach for college students. *Heliyon*, *10*(4), e25775. https://doi.org/10.1016/j.heliyon.2024.e25775

Carnevale, A. P., Jayasundera, T., & Gulish, A. (2016). *America's divided recovery: College haves and have-nots*. Georgetown University Center on Education and the Workforce. https://cew.georgetown.edu/resources/reports/

Cattell, R. B. (1987). Intelligence: Its structure, growth and action. Amsterdam, the Netherlands: Elsevier, North-Holland.

Center for Collegiate Mental Health (2020). 2019 annual report. Penn State University. https://ccmh.memberclicks.net/assets/docs/2019-CCMH-Annual-Report_3.17.20.pdf.

Cetin, B. (2015). Academic motivation and self-regulated learning in predicting academic achievement in college. *Journal of International Education Research 11*(2), 95-106.

Chan, M., Estève, D., Fourniols, J.-Y., Escribà, C., & Campo, E. (2012). Smart wearable systems: Current status and future challenges. *Artificial Intelligence in Medicine, 56*, 137–156. https://doi.org/10.1016/j.artmed.2012.09.003

Charles, N. E., Strong, S. J., Burns, L. C., Bullerjahn, M. R., & Serafine, K. M. (2021). Increased mood disorder symptoms, perceived stress, and alcohol use among college students during the COVID-19 pandemic. *Psychiatry research*, *296*, 113706. https://doi.org/10.1016/j.psychres.2021.113706

Choi, E., Lee, J., & Lee, S. A. (2022). Validation of the Korean version of the obsession with COVID-19 scale and the Coronavirus anxiety scale. *Death studies*, *46*(3), 608–614. https://doi.org/10.1080/07481187.2020.1833383

Cipolletta, S., Tedoldi, I., & Tomaino, S. C. M. (2024). A blended group intervention to promote social connectedness and wellbeing among international university students: an exploratory study. *Frontiers in psychology*, *15*, 1497544. https://doi.org/10.3389/fpsyg.2024.1497544

Clark, A. E., Nong, H., Zhu, H., & Zhu, R. (2021). Compensating for academic loss: Online learning and student performance during the COVID-19 pandemic. *China Economic Review, 68*, 101629. https://doi.org/10.1016/j.chieco.2021.101629

Clemmons, A., Lebovitz, L., Fulford, M., Greene, K., Franks, A., Branan, T., & Plake, K. I. (2022). Impact of the COVID-19 pandemic on faculty at research-intensive United States schools/colleges of pharmacy. *Currents in pharmacy teaching & learning*, *14*(2), 145–152. https://doi.org/10.1016/j.cptl.2021.11.018

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior, 24* (4), 385-396. https://doi.org/10.2307/2136404

Cole, J. (1974). The relationship of selected personality variables to academic achievement of average aptitude third graders. *The Journal of Educational Research, 67*(7), 329-333. Retrieved October 7, 2020, from http://www.jstor.org/stable/27536615

Colling, J., Wollschläger, R., Keller, U., Preckel, F., & Fischbach, A. (2022). Need for Cognition and its relation to academic achievement in different learning environments. *Learning and Individual Differences, 93*. https://doi.org/10.1016/j.lindif.2021.102110

Columb, D., Hussain, R., & O'Gara, C. (2020). Addiction psychiatry and COVID-19: Impact on patients and service provision. *Irish Journal of Psychological Medicine, 37*(3), 164–168. https://doi.org/10.1017/ipm.2020.47

Conroy, D. A., Hadler, N. L., Cho, E., Moreira, A., MacKenzie, C., Swanson, L. M., Burgess, H. J., Arnedt, J. T., & Goldstein, C. A. (2021). The effects of COVID-19 stay-at-home order on sleep, health, and working patterns: a survey study of US health care workers. *Journal of clinical sleep medicine : JCSM : official publication of the American Academy of Sleep Medicine*, *17*(2), 185–191. https://doi.org/10.5664/jcsm.8808

Copeland, W. E., McGinnis, E., Bai, Y., Adams, Z., Nardone, H., Devadanam, V., Rettew, J., & Hudziak, J. J. (2021). Impact of COVID-19 pandemic on college student mental health and wellness. *Journal of the American Academy of Child & Adolescent Psychiatry, 60*(1), 134–141. https://doi.org/10.1016/j.jaac.2020.08.466

Coutinho, S. A. (2007). The relationship between goals, metacognition, and academic success. *Educate*, *7*(1), 39–47. Retrieved from http://educatejournal.org/index.php/educate/article/view/116

Creamer, M., Foran, J., & Bell, R. (1995). The Beck Anxiety Inventory in a non-clinical sample. *Behaviour research and therapy*, *33*(4), 477–485. https://doi.org/10.1016/0005-7967(94)00082-u

Credé, M., & Kuncel, N. R. (2008). Study Habits, Skills, and Attitudes: The Third Pillar Supporting Collegiate Academic Performance. *Perspectives on psychological science : a journal of the Association for Psychological Science*, *3*(6), 425–453. https://doi.org/10.1111/j.1745-6924.2008.00089.x

Cullen, W., Gulati, G., & Kelly, B. D. (2020). Mental health in the COVID-19 pandemic. *QJM : monthly journal of the Association of Physicians*, *113*(5), 311–312. https://doi.org/10.1093/qjmed/hcaa110

Czeisler, M. É., Lane, R. I., Petrosky, E., Wiley, J. F., Christensen, A., Njai, R., Weaver, M. D., Robbins, R., Facer-Childs, E. R., Barger, L. K., Czeisler, C. A., Howard, M. E., & Rajaratnam, S. M. W. (2020). Mental health, substance use, and suicidal ideation during the COVID-19 pandemic—United States, June 24–30, 2020. *Morbidity and Mortality Weekly Report, 69*(32), 1049–1057. https://doi.org/10.15585/mmwr.mm6932a1

Dangin, D., Setyawan, A. H., & Hartati, E. (2023). Metacognitive awareness and self-regulated learning toward students' academic achievement: Prediction study. *International Journal of Social Science and Human Research*, *6*(11), 6759–6764. https://doi.org/10.47191/ijsshr/v6-i11-24

David, I., Schatz, E., Myroniuk, T. W., & Teti, M. (2022). "*COVID Is Another Layer of Problematic Things*": Change, Vulnerability, and COVID-19 among University Students. *International journal of environmental research and public health*, *19*(23), 15947. https://doi.org/10.3390/ijerph192315947

Dayan, P., & Niv, Y. (2008). Reinforcement learning: the good, the bad and the ugly. *Current opinion in neurobiology*, *18*(2), 185–196. https://doi.org/10.1016/j.conb.2008.08.003

Deary, I.J., Strand, S., Smith, P., & Fernandes, C. (2007). Intelligence and educational achievement. *Intell.*, *35,* 13–21.

DeBerard, M. S., Spielmans, G. I., & Julka, D. L. (2004). Predictors of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal, 38*(1), 66–80.

Didier, R., Kreiter, C. D., Buri, R., & Solow, C. (2006). Investigating the utility of a GPA institutional adjustment index. *Academic Medicine, 81*(10 Suppl), S52–S54.

Drummond, N., & Niv, Y. (2020). Model-based decision making and model-free learning. *Current Biology, 30*(15), R860–R865. https://doi.org/10.1016/j.cub.2020.06.051

Dubuc, M. M., Aubertin-Leheudre, M., & Karelis, A. D. (2022). Predictors of Academic Performance in High School Students: The Longitudinal ASAP Study. *International journal of exercise science, 15*(4), 616–631.

Duckworth, A. L., Tsukayama, E., & May, H. (2010). Establishing causality using longitudinal hierarchical linear modeling: An illustration predicting achievement from self-control. *Social Psychological and Personality Science*, *1*(4), 311–317. https://doi.org/10.1177/1948550609359707

Duckworth, A. L., Quirk, A., Gallop, R., Hoyle, R. H., Kelly, D. R., & Matthews, M. D. (2019). Cognitive and noncognitive predictors of success. *Proceedings of the National Academy of Sciences of the United States of America, 116*(47), 23499–23504. https://doi.org/10.1073/pnas.1910510116

Dumas, T. M., Ellis, W., & Litt, D. M. (2020). What Does Adolescent Substance Use Look Like During the COVID-19 Pandemic? Examining Changes in Frequency, Social Contexts, and Pandemic-Related Predictors. *The Journal of adolescent health : official publication of the Society for Adolescent Medicine*, *67*(3), 354–361. https://doi.org/10.1016/j.jadohealth.2020.06.018

Eisenberg, D., Downs, M. F., Golberstein, E., & Zivin, K. (2009). Stigma and help seeking for mental health among college students. *Medical care research and review: MCRR*, *66*(5), 522–541. https://doi.org/10.1177/1077558709335173

Ekstrom, R. B., French, J. W., & Harman, H. H. (1979). *Cognitive factors: Their identification and replication* (Multivariate Behavioral Research Monographs No. 79–2). American Psychological Association.

Eppinger, B., Goschke, T., & Musslick, S. (2021). Meta-control: From psychology to computational neuroscience. *Cognitive, Affective and Behavioral Neuroscience*, *21*(3), 447–452. https://doi.org/10.3758/s13415-021-00919-4

Eppinger, B., Walter, M., Heekeren, H. R., & Li, S. C. (2013). Of goals and habits: age-related and individual differences in goal-directed decision-making. *Frontiers in neuroscience*, *7*, 253. https://doi.org/10.3389/fnins.2013.00253

Evans, T. M., Bira, L., Gastelum, J. B., Weiss, L. T., & Vanderford, N. L. (2018). Evidence for a mental health crisis in graduate education. *Nature biotechnology*, *36*(3), 282–284. https://doi.org/10.1038/nbt.4089

Evans, C. J., Kirby, J. R., & Fabrigar, L. R. (2003). Approaches to learning, need for cognition, and strategic flexibility among university students. *British Journal of Educational Psychology, 73*(4), 507–528. https://doiorg.ezproxy.lsus.edu/10.1348/000709903322591217

Fahle, E. M., Kane, T. J., Patterson, T., & Reardon, S. F. (2023). School district and community factors associated with learning loss during the COVID-19 Pandemic, (May). Retrieved from https://cepr.harvard.edu/sites/hwpi.harvard.edu/files/cepr/files/explaining_covid_losses_5.23.pdf

Farrington, C. A., Roderick, M., Allensworth, E., Nagaoka, J., Keyes, T. S., Johnson, D. W., & Beechum, N. O. (2012). Teaching adolescents to become learners: The role of noncognitive factors in shaping school performance: A critical literature review. *Chicago: University of Chicago Consortium on Chicago School Research*, *June*.

Ferrer, J., Iglesias, E., Blanco-Gutiérrez, I., & Estavillo, J. (2023). Analyzing the impact of COVID-19 on the grades of university education: A case study with economics students. *Social sciences & humanities open*, *7*(1), 100428. https://doi.org/10.1016/j.ssaho.2023.100428

Fidrayani, F., Fauzan, F., Nahartini, D., Yuliani, A., & Latip, A. E. (2020). Analysis of goals, metacognition and academic achievement students' of Muhammadiyah Malang University. In *Proceedings of the 1st International Conference on Recent Innovations (ICRI 2018), 1,* 1248–1256. SciTePress. https://doi.org/10.5220/0009925712481256

Fleischhauer, M., Enge, S., Brocke, B., Ullrich, J., Strobel, A., & Strobel, A. (2010). Same or different? Clarifying the relationship of need for cognition to personality and Intelligence. *Personality and Social Psychology Bulletin. 36*(1), 82–96.

Follmer, D. J. (2018). Executive function and reading comprehension: A meta-analytic review. *Educational Psychologist, 53*(1), 42-60. https://doi.org/10.1080/00461520.2017.1309295

Frey, M. C., & Detterman, D. K. (2004). Scholastic Assessment or g? The relationship between the Scholastic Assessment Test and general cognitive ability. *Psychological science*, *15*(6), 373–378. https://doi.org/10.1111/j.0956-7976.2004.00687.x

Fruehwirth, J. C., Huang, L., Tompson, C. E., & Perreira, K. M. (2025). Mental Health Symptoms Among US College Students Before, Early, and Late Into the COVID-19 Pandemic: A Longitudinal Analysis. *The Journal of adolescent health : official publication of the Society for Adolescent Medicine*, *76*(2), 246–253. https://doi.org/10.1016/j.jadohealth.2024.09.026

Gadermann, A. M., Thomson, K. C., Scherer, L. D., & Richardson, C. G. (2020). Validation of the Perceived Stress Scale (PSS) for COVID-19 among individuals with high levels of anxiety and stress. *Journal of Mental Health, 29* (4), 1-9. https://doi.org/10.1080/09638237.2020.1799540

Garris, C. P., & Fleck, B. (2020). Student evaluations of transitioned-online courses during the COVID-19 pandemic. *Scholarship of Teaching and Learning in Psychology*, *7*(2), 247-261. DOI: 10.1037/stl0000229

Geary, D.C. (2011). Cognitive predictors of achievement growth in mathematics: A 5-year longitudinal study. *Dev.Psychol., 47*, 1539–1552.

Geiser, S., & Santelices, M. V. (2007). *Validity of high-school grades in predicting student success beyond the freshman year: High school record vs. standardized tests as indicators of four-year college outcomes* (Research & Occasional Paper Series No. CSHE.6.07). University of California, Berkeley, Center for Studies in Higher Education. https://files.eric.ed.gov/fulltext/ED502858.pdf

Ghose, R., Forati, A. M., & Mantsch, J. R. (2022). Impact of the COVID-19 pandemic on opioid overdose deaths: A spatiotemporal analysis. *Journal of Urban Health, 99*(2), 316–327. https://doi.org/10.1007/s11524-022-00610-0

González, G. M., Costello, C. R., La Tourette, T. R., Joyce, L. K., & Valenzuela, M. (1997). Bilingual Telephone-Assisted Computerized Speech-Recognition Assessment: Is a Voice-Activated Computer Program a Culturally and Linguistically Appropriate Tool for Screening Depression in English and Spanish? *Cultural Diversity and Mental Health, 3*(2), 93-111. http://dx.doi.org/10.1037/1099-9809.3.2.93

Grass, J., Strobel, A., & Strobel, A. (2017). Cognitive investments in academic success: The role of need for cognition at university. *Front. Psychol*. *8*, 790. doi: 10.3389/fpsyg.2017.00790.

Gray, D., Chang, Y., & Anderman, E. M. (2015). Conditional effects of mastery goal structure on changes in students' motivational beliefs: Need for cognition matters. *Learning and Individual Differences, 40,* 9-21.

Gul, F., & Shehzad, S. (2012). Relationship Between Metacognition, Goal Orientation and Academic Achievement. *Procedia - Social and Behavioral Sciences*, *47*, 1864–1868. https://doi.org/10.1016/j.sbspro.2012.06.914

Harding, A. B., Ramirez, M. R., Ryan, A. D., Xiong, B. N., Rosebush, C. E., & Woods-Jaeger, B. (2023). Impacts of COVID-19 on Stress in Middle School Teachers and Staff in Minnesota: An Exploratory Study Using Random Forest Analysis. *International journal of environmental research and public health*, *20*(17), 6698. https://doi.org/10.3390/ijerph20176698

Hawthorne, M. J., Cooper, A., Chavis, K., Burrell, T., & Evans, C. (2021). Ability and responsibility: Need for Cognition and study habits in academic achievement. *Research in Higher Education Journal, 39,* 1-3. Retrieved from http://www.aabri.com/copyright.html

Haynes, H., Henderson, M., Harris, C., and Cooney, D. (2024). *Persistence and Attainment of 2019–20 First-Time Postsecondary Students After 3 Years (NCES 2024-401).* U.S. Department of Education. Washington, DC: National Center for Education Statistics. https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2024401.

Hickey, B. A., Chalmers, T., Newton, P., Lin, C. T., Sibbritt, D., McLachlan, C. S., Clifton-Bligh, R., Morley, J., & Lal, S. (2021). Smart Devices and Wearable Technologies to Detect and Monitor Mental Health Conditions and Stress: A Systematic Review. *Sensors (Basel, Switzerland)*, *21*(10), 3461. https://doi.org/10.3390/s21103461

Hill, B. D., Foster, J. D., Elliott, E. M., Shelton, J. T., McCain, J., & Gouvier, W. D. (2013). Need for cognition is related to higher general intelligence, fluid intelligence, and crystallized intelligence, but not working memory. *Journal of Research in Personality, 47*(1), 22–25. https://doi.org/10.1016/j.jrp.2012.11.001

Hu, K., Godfrey, K., Ren, Q., Wang, S., Yang, X., & Li, Q. (2022). The impact of the COVID-19 pandemic on college students in USA: Two years later. *Psychiatry research*, *315*, 114685. https://doi.org/10.1016/j.psychres.2022.114685

Holtzman, M., Whitehead, E., & Welch, A. (2023). Adjusting Class Policies amid a Pandemic: How Lessons Learned During COVID-19 Can Help Faculty Prepare for Other Institution-Wide Crises. *Teaching and Learning Inquiry*, *11*. https://doi.org/10.20343/teachlearninqu.11.7

Izumi, T., Sukhwani, V., Surjan, A., & Shaw, R. (2021). Managing and responding to pandemics in higher educational institutions: Initial learning from COVID-19. *International Journal of Disaster Resilience in the Built Environment, 12*(1), 51–66. https://doi.org/10.1108/IJDRBE-06-2020-0054.

Jao, N. C., Robinson, L. D., Kelly, P. J., Ciecierski, C. C., & Hitsman, B. (2019). Unhealthy behavior clustering and mental health status in United States college students. *Journal of American college health*, *67*(8), 790–800. https://doi.org/10.1080/07448481.2018.1515744

Jeffers, A., Meehan, A. A., Barker, J., Asher, A., Montgomery, M. P., Bautista, G., Ray, C. M., Laws, R. L., Fields, V. L., Radhakrishnan, L., Cha, S., Christensen, A., Dupervil, B., Verlenden, J. V., Cassell, C. H., Boyer, A., DiPietro, B., Cary, M., Yang, M., Mosites, E., & Marcus, R. (2022). Impact of social isolation during the COVID-19 pandemic on mental health, substance use, and homelessness: Qualitative interviews with behavioral health providers. *International Journal of Environmental Research and Public Health, 19*(19), 12120. https://doi.org/10.3390/ijerph191912120

Johnson, V. E. (2003). *Grade inflation: A crisis in college education*. Springer.

Johnson, C. S., McLeod, P. J., Sharpe, D., & Johnston, E. M. (2008). Differences among core dimensions of the Centre for Epidemiological Studies Depression (CES-D) scale across age and gender groups. *Canadian Journal of Community Mental Health, 27*(1), 79-91.

Karadag E. (2021). Effect of COVID-19 pandemic on grade inflation in higher education in Turkey. *PloS one*, *16*(8), e0256688. https://doi.org/10.1371/journal.pone.0256688

Keller, U., Strobel, A., Wollschläger, R., Greiff, S., Martin, R., Vainikainen, M.P., & Preckel, F. (2019). A need for cognition scale for children and adolescents: Structural analysis and measurement invariance. *European Journal of Psychological Assessment, 35*(1), 137–149. https://doi.org/10.1027/1015-5759/a000370

Keng, S.-H. (2023). The effect of soft skills on academic outcomes. *The B.E. Journal of Economic Analysis & Policy, 24*(1). https://doi.org/10.1515/bejeap-2022-0342

Kobrin, J. L., Patterson, B. F., Shaw, E. J., Mattern, K. D., & Barbuti, S. M. (2008). *Validity of the SAT® for predicting first-year college grade point average* (College Board Research Report No. 2008-5). College Board. https://files.eric.ed.gov/fulltext/ED563202.pdf

Komarraju, M., Karau, S. J., & Schmeck, R. R. (2009). Role of the big five personality traits in predicting college students' academic motivation and achievement. *Learning and Individual Differences*, *19*(1), 47–52

Kool, W., Gershman, S. J., & Cushman, F. A. (2017). Cost-Benefit Arbitration Between Multiple Reinforcement-Learning Systems. *Psychological science, 28*(9), 1321–1333. https://doi.org/10.1177/0956797617708288

Kramer, A.-W., Van Duijvenvoorde, A. C. K., Krabbendam, L., & Huizenga, H. M. (2021). Individual differences in adolescents' willingness to invest cognitive effort: Relation to need for cognition, motivation and cognitive capacity. *Cognitive Development, 57,* Article 100978. https://doi.org/10.1016/j.cogdev.2020.100978

Kuhfeld, M., Lewis, K., & Peltier, T. (2023). Reading achievement declines during the COVID-19 pandemic: evidence from 5 million U.S. students in grades 3-8. *Reading and writing*, *36*(2), 245–261. https://doi.org/10.1007/s11145-022-10345-8

Kuhfeld, M., Soland, J., & Lewis, K. (2022). Test Score Patterns Across Three COVID-19-Impacted School Years. *Educational Researcher, 51*(7), 500-506. https://doi.org/10.3102/0013189X221109178

LaGuardia Community College, Office of Institutional Research and Assessment. (2022, January). *A report on the impact of the pandemic on student outcomes: December 2021*. LaGuardia Community College. https://www.laguardia.edu/uploadedfiles/main_site/content/ir/docs/the-impact-of-the-covid-19-pandemic-december%202021.pdf

Laidra, K., Pullmann, H., & Allik, J. (2007). Personality and intelligence as predictors of academic achievement: A cross-sectional study from elementary to secondary school. Pers. *Individ. Differ.*, *42*, 441–451.

Lavrijsen, J., Aerts, E., Preckel, F., Ramos, A., & Verschueren, K. (2024). Becoming a "hungry mind": Stability and change in need for cognition across adolescence. *Journal of Intelligence, 12*(10), Article 103. https://doi.org/10.3390/jintelligence12100103

Lee, S. A. (2020). Coronavirus anxiety scale: a brief mental health screener for COVID-19 related anxiety. *Death Stud. 44*, 393–401. doi: 10.1080/07481187.2020.1748481

Li, H. Y., Cao, H., Leung, D. Y. P., & Mak, Y. W. (2020). The Psychological Impacts of a COVID-19 Outbreak on College Students in China: A Longitudinal Study. *International journal of environmental research and public health*, *17*(11), 3933. https://doi.org/10.3390/ijerph17113933

Lieder, F., & Griffiths, T. L. (2017). Strategy selection as rational metareasoning. *Psychological Review, 124*(6), 762–794. https://doi.org/10.1037/rev0000075

Lindenberger, U., Mayr, U., & Kliegl, R. (1993). Speed and intelligence in old age. *Psychology and Aging, 8*(2), 207–220. https://doi.org/10.1037/0882-7974.8.2.207

Liu, Q., & Nesbit, J. C. (2024). The relation between need for cognition and academic achievement: A meta-analysis. *Review of Educational Research, 94*(2), 155–192. https://doi.org/10.3102/00346543231160474

Liu, C. H., Stevens, C., Wong, S. H. M., Yasui, M., & Chen, J. A. (2019). The prevalence and predictors of mental health diagnoses and suicide among U.S. college students: Implications for addressing disparities in service use. *Depression and anxiety*, *36*(1), 8–17. https://doi.org/10.1002/da.22830

Lowe, C., Keown-Gerrard, J., Ng, C. F., Gilbert, T. H., & Ross, K. M. (2023a). COVID-19 pandemic mental health trajectories: Patterns from a sample of Canadians primarily recruited from Alberta and Ontario. *Canadian Journal of Behavioural Science / Revue canadienne des sciences du comportement, 55*(2), 113–129. https://doi.org/10.1037/cbs0000313

Lowe, C., Rafiq, M., MacKay, L. J., Letourneau, N., Ng, C. F., Keown-Gerrard, J., Gilbert, T., & Ross, K. M. (2023b). Impact of the COVID-19 Pandemic on Canadian Social Connections: A Thematic Analysis. *Journal of social and personal relationships*, *40*(1), 76–101. https://doi.org/10.1177/02654075221113365

Lubben, J. E., Blozik, E., Gillmann, G., & Borkowski, L. (2006). The Lubben Social Network Scale (LSNS): A tool for assessing social networks and social support among older adults. *Journal of Gerontology: Social Sciences, 61* (4), 227-238. https://doi.org/10.1093/geronb/61.4.S227

Luo, D., Thompson, L. A., & Detterman, D. K. (2003). The causal factor underlying the correlation between psychometric g and scholastic performance. *Intelligence, 31*(1), 67−83.

Luo, D., Thompson, L.A., Detterman, & D.K. (2006). The criterion validity of tasks of basic cognitive processes. *Intell., 34,* 79–120.

Luong, C., Strobel, A., Wollschläger, R., Greiff, S., Vainikainen, M.-P., & Preckel, F. (2017). Need for cognition in children and adolescents: Behavioral correlates and relations to academic achievement and potential. *Learning and Individual Differences, 53,* 103–113. https://doi.org/10.1016/j.lindif.2016.10.019

Ma, J., & Pender, M. (2023). *Education pays 2023: The benefits of higher education for individuals and society*. New York: College Board. https://research.collegeboard.org/trends/education-pays

Maghalian, M., Ghafari, R., Osouli Tabrizi, S., Nikkhesal, N., & Mirghafourvand, M. (2023). Predictors of Academic Success in Students of Tabriz University of Medical Sciences: A Cross-Sectional Study. *Journal of advances in medical education & professionalism*, *11*(3), 155–163. https://doi.org/10.30476/JAMP.2022.96841.1725

Mahdy M. A. A. (2020). The Impact of COVID-19 Pandemic on the Academic Performance of Veterinary Medical Students. *Frontiers in veterinary science*, *7*, 594261. https://doi.org/10.3389/fvets.2020.594261

Malanchini, M., Engelhardt, L. E., Grotzinger, A. D., Harden, K. P., & Tucker-Drob, E. M. (2019). "Same but different": Associations between multiple aspects of self-regulation, cognition, and academic abilities. *Journal of personality and social psychology*, *117*(6), 1164–1188. https://doi.org/10.1037/pspp0000224

Malykh, S., Lysenkova, I., Zakharov, I., & Tikhomirova, T. (2017). Cognitive Predictors Of Academic Achievement At High School Age: Cross-Cultural Study. In S. B. Malykh, & E. V. Nikulchev (Eds.), Psychology and Education - ICPE 2017, vol 33. European Proceedings of Social and Behavioural Sciences (pp. 235-247). Future Academy. https://doi.org/10.15405/epsbs.2017.12.23

Matthews G. (2018). Cognitive-Adaptive Trait Theory: A Shift in Perspective on Personality. *Journal of personality*, *86*(1), 69–82. https://doi.org/10.1111/jopy.12319

Meier, E., Vogl, K., & Preckel, F. (2014). Motivational characteristics of students in gifted classes: The pivotal role of need for cognition. *Learning and Individual Differences, 33,* 39–46. https://doi.org/10.1016/j.lindif.2014.04.006

Morosanova, V. I., Bondarenko, I. N., & Fomina, T. G. (2022). Conscious self-regulation, motivational factors, and personality traits as predictors of students' academic performance: A linear empirical model. *Psychology in Russia: State of the Art, 15*(4), 170–187. https://doi.org/10.11621/PIR.2022.0411

Moss, R. H., Kelly, B., Bird, P. K., & Pickett, K. E. (2023). Examining individual social status using the MacArthur Scale of Subjective Social Status: Findings from the Born in Bradford study. *SSM - Population Health, 23*, 101463. https://doi.org/10.1016/j.ssmph.2023.101463

Mundt, J. C., Marks, I. M., Shear, M. K., and Greist, J. H. (2002). The work and social adjustment scale: a simple measure of impairment in functioning. *Br. J. Psychiatry 180*, 461–464. doi: 10.1192/bjp.180.5.461

National Academies of Sciences, Engineering, and Medicine. (2023). Social, emotional, and behavioral effects (E. P. Backes, J. A. Gootman, & T. R. Coker, Eds.). In *Addressing the long-term effects of the COVID-19 pandemic on children and families* (Chapter 3). National Academies Press. https://www.ncbi.nlm.nih.gov/books/NBK594927/

Neigel, A. R., Behairy, S., & Szalma, J. L. (2017). Need for cognition and motivation differentially contribute to student performance. *Journal of Cognitive Education and Psychology, 16*(2), 144–156. https://doi-org.ezproxy.lsus.edu/10.1891/1945-8959.16.2.144

Ogles, B.M., France, C.R., Lunnen, K.M., Bell, T.M., & Goldfarb, M. (1998). Computerized depression screening and awareness. *Community Mental Health Journal*, *34*(1), 27–38.

Otto, A. R., & Daw, N. D. (2019). The opportunity cost of time modulates cognitive effort. *Neuropsychologia, 123*, 92–105. https://doi.org/10.1016/j.neuropsychologia.2018.05.006

Otto, A. R., Skatova, A., Madlon-Kay, S., & Daw, N. D. (2015). Cognitive control predicts use of model-based reinforcement learning. *Journal of cognitive neuroscience, 27*(2), 319–333. https://doi.org/10.1162/jocn_a_00709

Parker, K., Minkin, R., & Bennett, J. (2020). *Economic fallout from COVID-19 continues to hit lower-income Americans the hardest*. Pew Research Center. https://www.pewresearch.org/social-trends/2020/09/24/economic-fallout-from-covid-19-continues-to-hit-lower-income-americans-the-hardest/

Pascual, A.C., Moyano Muñoz, N., & Quílez Robres, A. (2019). The Relationship Between Executive Functions and Academic Performance in Primary Education: Review and Meta-Analysis. *Frontiers in psychology*, *10*, 1582. https://doi.org/10.3389/fpsyg.2019.01582

Pelham, W. E., 3rd, Tapert, S. F., Gonzalez, M. R., McCabe, C. J., Lisdahl, K. M., Alzueta, E., Baker, F. C., Breslin, F. J., Dick, A. S., Dowling, G. J., Guillaume, M., Hoffman, E. A., Marshall, A. T., McCandliss, B. D., Sheth, C. S., Sowell, E. R., Thompson, W. K., Van Rinsveld, A. M., Wade, N. E., & Brown, S. A. (2021). Early Adolescent Substance Use Before and During the COVID-19 Pandemic: A Longitudinal Survey in the ABCD Study Cohort. *The Journal of adolescent health : official publication of the Society for Adolescent Medicine*, *69*(3), 390–397. https://doi.org/10.1016/j.jadohealth.2021.06.015

Peng, P., & Kievit, R. A. (2020). The Development of Academic Achievement and Cognitive Abilities: A Bidirectional Perspective. *Child Development Perspectives, 14*(1), 15–20. https://doi.org/10.1111/cdep.12352

Peng, P., Wang, T., Wang, C., & Lin, X. (2019). A meta-analysis on the relation between fluid intelligence and reading/mathematics: Effects of tasks, age, and social economics status. *Psychological Bulletin, 145,* 189–236. https://doi.org/10.1037/bul0000182

Pfefferbaum, B., & North, C. S. (2020). Mental Health and the Covid-19 Pandemic. *The New England journal of medicine*, *383*(6), 510–512. https://doi.org/10.1056/NEJMp2008017

Plant, E. A., Ericsson, K. A., Hill, L., & Asberg, K. (2005). Why study time does not predict grade point average across college students: Implications of deliberate practice for academic performance. *Contemporary Educational Psychology, 30*(1), 96–116.

Radloff, L.S. (1977). The CES-D Scale: a self-report depression scale for research in the general population. *Applied Psychological Measurement, 1*, 385-401.

Reyes-Portillo, J. A., Masia Warner, C., Kline, E. A., Bixter, M. T., Chu, B. C., Miranda, R., Nadeem, E., Nickerson, A., Ortin Peralta, A., Reigada, L., Rizvi, S. L., Roy, A. K., Shatkin, J., Kalver, E., Rette, D., Denton, E. G., & Jeglic, E. L. (2022). The Psychological, Academic, and Economic Impact of COVID-19 on College Students in the Epicenter of the Pandemic. *Emerging adulthood (Print)*, *10*(2), 473–490. https://doi.org/10.1177/21676968211066657

Richardson, M., Abraham, C., Anderson, J. C., Gerbing, D. W., Bandalos, D. L., Finney, S. J., et al. (2009). Conscientiousness and achievement motivation predict performance. *Eur. J. Personal. 23*, 589–605. doi: 10.1002/per.732

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin, 138*(2), 353–387. https://doi-org.ezproxy.lsus.edu/10.1037/a0026838

Riepenhausen, A., Haller, H., & Meyer, B. (2020). Coronavirus Anxiety Scale: A brief measure of anxiety in the context of the COVID-19 pandemic. *Journal of Anxiety, Stress, & Coping, 33*(3), 233-239. https://doi.org/10.1080/10615806.2020.1752226

Roberts, R.E., Vernon, S.W., & Rhoades, H.M. (1989). Effects of Language and Ethnic Status on Reliability and Validity of the Center for Epidemiologic Studies Depression Scale with Psychiatric Patients. *The Journal of Nervous and Mental Disease, 177*(10), 581-592.

Robinson, N. M. (2004). Academic motivation and its relationship to personality variables and achievement. *Dissertation Abstracts International: Section B: The Sciences and Engineering, 64*(9-B), 4632.

Rodic, M., Zhou, X., Tikhomirova, T., Wei, W., Malykh, S., Ismatulina, V., Sabirova, E., Davidova, Y., Tosto, M. G., Lemelin, J. P., & Kovas, Y. (2015). Cross-cultural investigation into cognitive underpinnings of individual differences in early arithmetic. *Developmental science*, *18*(1), 165–174. https://doi.org/10.1111/desc.12204

Rohde, T. E., & Thompson, L. A. (2007). Predicting academic achievement with cognitive ability. *Intelligence*, *35*(1), 83–92. https://doi.org/10.1016/j.intell.2006.05.004

Ruffing, S., Wach, F. S., Spinath, F. M., Brünken, R., & Karbach, J. (2015). Learning strategies and general cognitive ability as predictors of gender- specific academic achievement. *Frontiers in psychology*, *6*, 1238. https://doi.org/10.3389/fpsyg.2015.01238

Rutkowska A. (2022). Remote Interventions to Support Students' Psychological Well-Being during the COVID-19 Pandemic: A Narrative Review of Recent Approaches. *International journal of environmental research and public health, 19*(21), 14040. https://doi.org/10.3390/ijerph192114040

Sallie, S. N., Ritou, V., Bowden-Jones, H., & Voon, V. (2020). Assessing international alcohol consumption patterns during isolation from the COVID-19 pandemic using an online survey: highlighting negative emotionality mechanisms. *BMJ open*, *10*(11), e044276. https://doi.org/10.1136/bmjopen-2020-044276-044276

Sandra, D. A., & Otto, A. R. (2018). Cognitive capacity limitations and Need for Cognition differentially predict reward-induced cognitive effort expenditure. *Cognition*, *172*, 101–106. https://doi.org/10.1016/j.cognition.2017.12.004

Sauer, N., Sałek, A., Szlasa, W., Ciecieląg, T., Obara, J., Gaweł, S., Marciniak, D., & Karłowicz-Bodalska, K. (2022). The impact of COVID-19 on the mental well-being of college students. *International Journal of Environmental Research and Public Health, 19*(9), 5089. https://doi.org/10.3390/ijerph19095089

Shean, G., & Baldwin, G. (2008). Sensitivity and specificity of depression questionnaires in a college-age sample. *The Journal of Genetic Psychology, 169*, 281-288.

Shi, Y., & Qu, S. (2021). Cognition and academic performance: Mediating role of personality characteristics and psychology health. *Frontiers in Psychology, 12,* Article 774548. https://doi.org/10.3389/fpsyg.2021.774548

Shi, Y., & Qu, S. (2022a). Analysis of the effect of cognitive ability on academic achievement: Moderating role of self-monitoring. *Frontiers in psychology*, *13*, 996504. https://doi.org/10.3389/fpsyg.2022.996504

Shi, Y., & Qu, S. (2022b). The effect of cognitive ability on academic achievement: The mediating role of self-discipline and the moderating role of planning. *Frontiers in psychology*, *13*, 1014655. https://doi.org/10.3389/fpsyg.2022.1014655

Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin, 119*(1), 3–22. https://doi.org/10.1037/0033-2909.119.1.3

Son, C., Hegde, S., Smith, A., Wang, X., & Sasangohar, F. (2020). Effects of COVID-19 on college students' mental health in the United States: Interview survey study. *Journal of Medical Internet Research, 22*(9), e21279. DOI: 10.2196/21279

Sternberg, R. J., Kaufman, J. C., & Grigorenko, E. L. (2008). Applied intelligence. New York, NY: Cambridge University Press.

Strenze, T. (2007). Intelligence and socioeconomic success: A meta-analytic review of longitudinal research. *Intelligence, 35*(5), 401–426.

Süß, H.-M., Oberauer, K., Wittmann, W. W., Wilhelm, O., & Schulze, R. (2002). Working-memory capacity explains reasoning ability--and a little bit more. *Intelligence, 30*(3), 261–288. https://doi.org/10.1016/S0160-2896(01)00100-3

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction*. MIT Press.

Swendsen, J., Conway, K. P., Degenhardt, L., Glantz, M., Jin, R., Merikangas, K. R., Sampson, N., & Kessler, R. C. (2010). Mental disorders as risk factors for substance use, abuse and dependence: results from the 10-year follow-up of the National Comorbidity Survey. *Addiction (Abingdon, England)*, *105*(6), 1117–1128. https://doi.org/10.1111/j.1360-0443.2010.02902.x

Theurel, A., Witt, A., & Shankland, R. (2022). Promoting University Students' Mental Health through an Online Multicomponent Intervention during the COVID-19 Pandemic.

International journal of environmental research and public health, *19*(16), 10442. https://doi.org/10.3390/ijerph191610442

Tikhomirova, T., Kuzmina, Y., Lysenkova, I., & Malykh, S. (2019). Development of approximate number sense across the elementary school years: A cross-cultural longitudinal study. *Developmental science*, *22*(4), e12823. https://doi.org/10.1111/desc.12823

Tikhomirova, T. N., Malykh, A. S., Lysenkova, I. A., & Malykh, S. B. (2021). Cross-cultural Analysis of Models of the Relationship between the Cognitive Abilities and Academic Achievement in Primary School Education. *Psychology in Russia : state of the art*, *14*(4), 94–110. https://doi.org/10.11621/pir.2021.0407

Tikhomirova, T., Malykh, A., & Malykh, S. (2020). Predicting Academic Achievement with Cognitive Abilities: Cross-Sectional Study across School Education. *Behavioral sciences (Basel, Switzerland)*, *10*(10), 158. https://doi.org/10.3390/bs10100158

Tikhomirova, T.N., Malykh, S.B., Tosto, M.G., & Kovas, Y.V. (2014). Cognitive characteristics and mathematical achievement in high school students: Cross-cultural analyses. *Psihologicheskij Zhurnal, 35,* 41–53.

Unger, K. (2007). *Handbook on supported education: Providing services for students with psychiatric disabilities*. BookSurge Publishing.

U.S. Bureau of Labor Statistics. (2024, April). *Education pays, 2023*. *Career Outlook*.https://www.bls.gov/careeroutlook/2024/data-on-display/education-pays.htm

van der Wel, P., & van Steenbergen, H. (2018). Pupil dilation as an index of effort in cognitive control tasks: A review. *Psychonomic bulletin & review*, *25*(6), 2005–2015. https://doi.org/10.3758/s13423-018-1432-y

Vautier, A., Enns, K., & Cadaret, C. (2023). Impacts of the COVID-19 pandemic on student performance and perceptions of learning. *NACTA Journal, 67*(1). https://doi.org/10.56103/nactaj.v67i1.94

Verbitskaya, L.A., Zinchenko, Y.P., Malykh, S.B., Gaidamashko, I.V., Kalmyk, O.A., & Tikhomirova, T.N. (2020). Cognitive Predictors of Success in Learning Russian Among Native Speakers of High School Age in Different Educational Systems. *Psychol. Russ. State Art*, *13*, 2–15.

Vilagut, G., Forero, C. G., Barbaglia, G., & Alonso, J. (2016). Screening for Depression in the General Population with the Center for Epidemiologic Studies Depression (CES-D): A Systematic Review with Meta-Analysis. *PloS one*, *11*(5), e0155431. doi:10.1371/journal.pone.0155431

Vo, A. T., Patton, T., Peacock, A., Larney, S., & Borquez, A. (2022). Illicit Substance Use and the COVID-19 Pandemic in the United States: A Scoping Review and Characterization of Research Evidence in Unprecedented Times. *International journal of environmental research and public health*, *19*(14), 8883. https://doi.org/10.3390/ijerph19148883

Volkow, N. D. (2020). Collision of the COVID-19 and addiction epidemics. *Annals of Internal Medicine, 173*(1), 61–62. https://doi.org/10.7326/M20-1212

Wainwright, J. J., Mikre, M., Whitley, P., Dawson, E., Huskey, A., Lukowiak, A., & Giroir, B. P. (2020). Analysis of Drug Test Results Before and After the US Declaration of a National Emergency Concerning the COVID-19 Outbreak. *JAMA*, *324*(16), 1674–1677. https://doi.org/10.1001/jama.2020.17694

Walberg, H. J., Fraser, B. J., & Welch, W. W. (1986). Assessing student learning environments: Relationships among teaching practices, student attitudes, and cognitive outcomes. *Journal of Educational Psychology, 78*(2), 210–219.

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C. S., & Ho, R. C. (2020). Immediate Psychological Responses and Associated Factors during the Initial Stage of the 2019 Coronavirus Disease (COVID-19) Epidemic among the General Population in China. *International journal of environmental research and public health*, *17*(5), 1729. https://doi.org/10.3390/ijerph17051729

Weissgerber, S. C., Reinhard, M.-A., & Schindler, S. (2018). Learning the hard way: Need for cognition influences attitudes toward and self-reported use of desirable difficulties. *Educational Psychology, 38*(2), 176–202. https://doi.org/10.1080/ 01443410.2017.1387644

Weissman, M.M, Sholomskas, D., Pottenger, M., Prusoff, B.A., & Locke, B.A. (1977). Assessing depressive symptoms in five psychiatric populations: a validation study, *American Journal of Epidemiology*, *106*, (31), 203–214.

Welsh, J. W., Shentu, Y., & Sarvey, D. B. (2019). Substance Use Among College Students. *Focus (American Psychiatric Publishing)*, *17*(2), 117–127. https://doi.org/10.1176/appi.focus.20180037

White, H. R., Stevens, A. K., Hayes, K., & Jackson, K. M. (2020). Changes in Alcohol Consumption Among College Students Due to COVID-19: Effects of Campus Closure and Residential Change. *Journal of studies on alcohol and drugs*, *81*(6), 725–730. https://doi.org/10.15288/jsad.2020.81.725

WHO ASSIST Working Group (2002). The Alcohol, Smoking and Substance Involvement Screening Test (ASSIST): development, reliability and feasibility. *Addiction (Abingdon, England)*, *97*(9), 1183–1194. https://doi.org/10.1046/j.1360-0443.2002.00185.x

Xiong, J., Lipsitz, O., Nasri, F., Lui, L. M. W., Gill, H., Phan, L., Chen-Li, D., Iacobucci, M., Ho, R., Majeed, A., & McIntyre, R. S. (2020). Impact of COVID-19 pandemic on mental health in the general population: A systematic review. *Journal of affective disorders*, *277*, 55–64. https://doi.org/10.1016/j.jad.2020.08.001

Yan, X., & Otto, A. R. (2020). Cognitive effort investment and opportunity costs in strategic decision-making: An individual differences examination. *Personality and Individual Differences*, *167*, Article 110283. https://doi.org/10.1016/j.paid.2020.110283

Yang, Y., Li, W., Zhang, Q., Zhang, L., Cheung, T., & Xiang, Y. T. (2020). Mental health services for older adults in China during the COVID-19 outbreak. *The lancet. Psychiatry*, *7*(4), e19. https://doi.org/10.1016/S2215-0366(20)30079-1

Zaboski, B. A., Kranzler, J. H., & Gage, N. A. (2018). Meta-analysis of the relationship between academic achievement and broad abilities of the Cattell-Horn-Carroll theory. *Journal of School Psychology, 71*, 42–56. https://doi.org/10.1016/j.jsp.2018.10.001

Zamarro, G., Camp, A., Fuchsman, D., & McGee, J. (2022). Understanding How Covid-19 Has Changed Teachers' Chances of Remaining in the Classroom. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4047354

Zheng, A., Tucker-Drob, E.M., & Briley, D.A. (2019). National Gross Domestic Product, Science Interest, and Science Achievement: A Direct Replication and Extension of the Tucker-Drob, Cheung, and Briley (2014) Study. *Psychol. Sci., 30,* 776–788.

Zimmerman, B. J. (2011). Motivational sources and outcomes of self-regulated learning and performance. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 49–64). Routledge/Taylor & Francis Group.

Zisman, C., & Ganzach, Y. (2022). The claim that personality is more important than intelligence in predicting important life outcomes has been greatly exaggerated. *Intelligence, 92*, 101631. https://doi.org/10.1016/j.intell.2022.101631

Appendix A

Supplementary Materials for Study 2

Supplemental Table A.1
Descriptive statistics by drug type

Variable	N	Range	Mean (SD)
Tobacco Use T1	125	0-14	1.30 (2.91)
Tobacco Use T2	123	0-27	2.76 (5.23)
Alcohol Use T1	125	0-14	3.66 (3.15)
Alcohol Use T2	122	0-27	6.26 (5.53)
Cannabis Use T1	125	0-13	1.78 (3.09)
Cannabis Use T2	124	0-10	1.43 (2.21)
Cocaine Use T1	121	0-8	0.95 (1.50)
Cocaine Use T2	125	0-8	0.49 (0.44)
Amphetamine Use T1	125	0-11	0.66 (1.93)
Amphetamine Use T2	121	0-11	0.52 (1.74)
Inhalants Use T1	121	0-6	0.09 (0.71)
Inhalants Use T2	121	0-6	0.09 (0.71)
Sedatives Use T1	125	0-9	0.66 (2.04)
Sedatives Use T2	125	0-9	0.52 (1.93)
Hallucinogens Use T1	125	0-6	0.16 (0.70)

Hallucinogens Use T2	122	0-14	0.15 (2.10)
Opioids Use T1	125	0-6	0.05 (0.31)
Opioids Use T2	125	0-6	0.06 (0.32)
Other Drugs Use T1	125	0-4	0.03 (0.36)
Other Drugs Use T2	120	0-7	0.17 (0.96)

Note. The table presents means, standard deviations, and observed ranges for self-reported use of 10 different drug categories, measured using the Alcohol, Smoking and Substance Involvement Screening Test (ASSIST) at both Timepoint 1 (T1) and Timepoint 2 (T2).

Supplemental Table A.2
Descriptive statistics for the prevalence of psychiatric disorders

Psychiatric Condition	N (primary diagnosis)	Listed as co-morbidity
Anxiety Disorders	13 (10.5%)	38
Bipolar and other related disorders	1 (0.81%)	1
Depressive Disorders	34 (27%)	1
OCD and related disorders (Body Dysmorphic Disorder, Hoarding disorder, Trichotillomania)	2 (1.6%)	5
Schizophrenia and other psychotic disorders	1 (0.81%)	0
Sleep-Wake disorders	1 (0.81%)	3
Substance-Related and Addictive disorders	0	2
No diagnosis	73	
Total	124	

Note. Sample breakdown of psychiatric diagnosis by type. N=51 participants (41% of the sample) reported struggling with a psychiatric condition. Frequencies of each diagnosis are reported (i.e., number of participants and the percent of sample). The first column represents a primary diagnosis, the second column specifies whether disorders were listed as co-morbidities. N=25 endorsed single psychiatric condition, while N=26 listed themselves as having 2 disorders or more.

Supplemental Table A.3

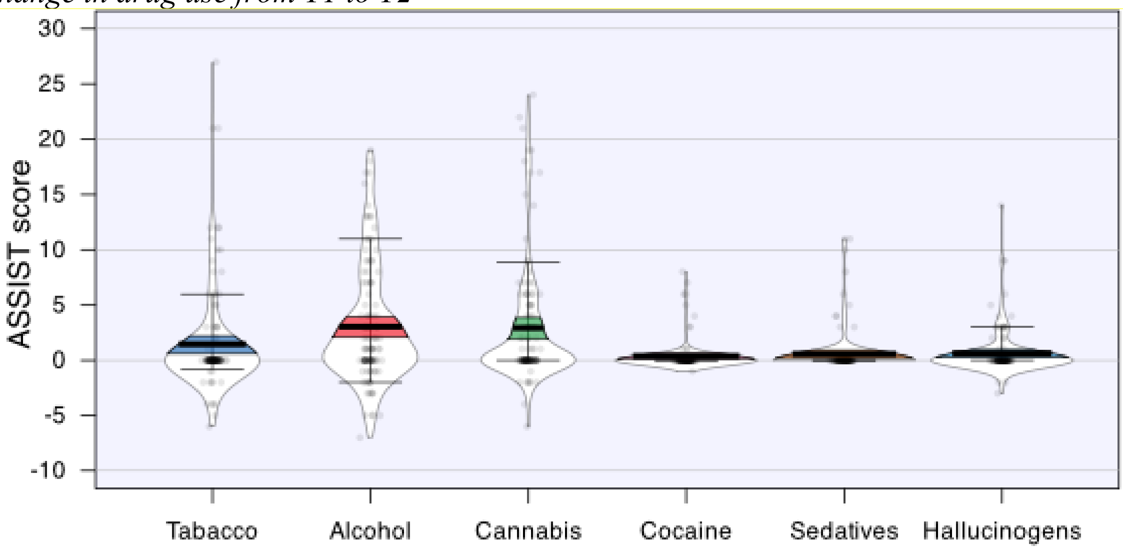
Descriptive Statistics for Supplementary Academic Variables Assessed During the Pandemic

Variable	N	Range	Mean (SD)
Satisfaction with academics	125	0-100	48.21 (23.13)
Professor flexibility	125	0-100	55.05 (22.59)
Change in online academic activity	125	0-131	77 (27.52)

Note. This table presents means, standard deviations, and observed ranges for three variables capturing students' academic experiences during the COVID-19 pandemic. *Satisfaction with academics* was assessed using two 0–100 scale items evaluating students' satisfaction with Concordia University's academic services and course quality during the pandemic. Higher scores indicate greater satisfaction. *Professor flexibility* was measured via a single item asking how flexible and accommodating students perceived their professors to be during the pandemic (0–100 scale). Higher scores reflect greater perceived flexibility. *Change in online academic activity* was calculated by subtracting the percentage of academic activities conducted online before the pandemic from the percentage during the pandemic, with higher scores indicating greater shifts toward online learning.

Supplemental Figure A.1

Change in drug use from T1 to T2

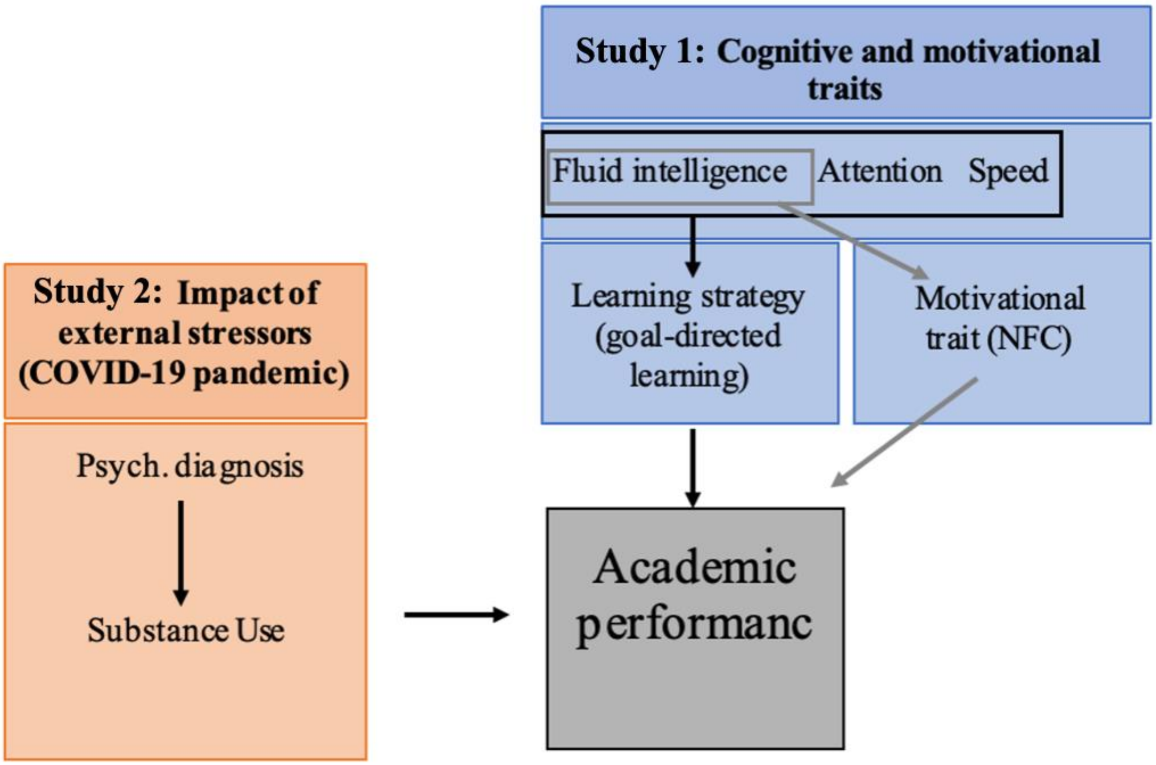


Note. Violin plots depicting the distribution of change scores for self-reported drug use (ASSIST scores) from T1 to T2 for each substance category. Each plot shows the probability density of the change scores, with overlaid boxplots representing the median, interquartile range, and potential outliers.

Appendix B

Figure B.1

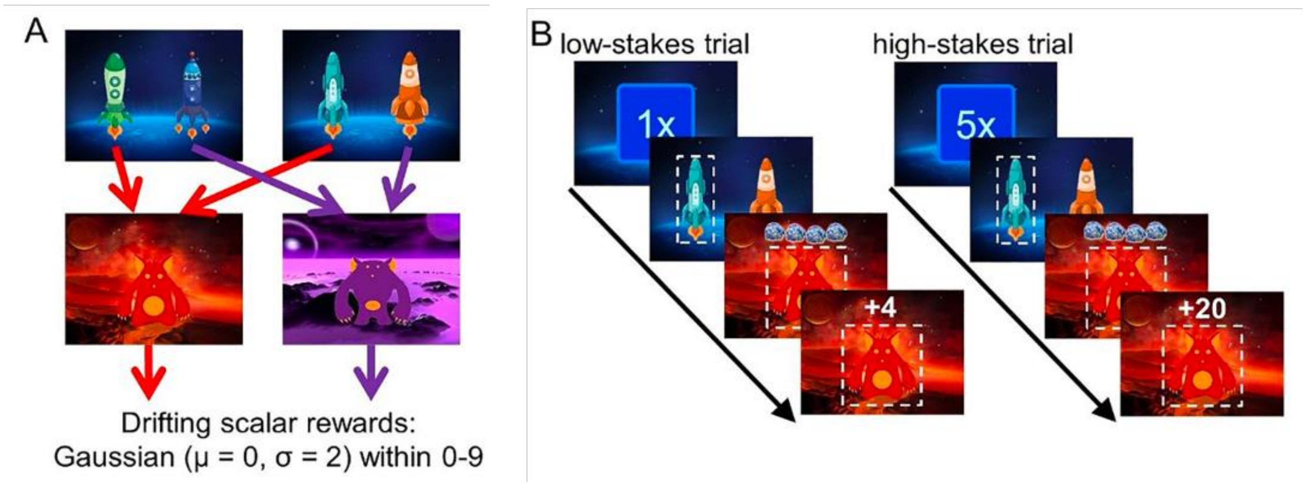
Understanding Academic Performance Through Cognitive, Motivational, and Contextual Lenses



Note. Conceptual framework illustrating multi-level contributors to academic performance. Core cognitive ability (e.g., fluid intelligence) did not directly predict academic outcomes but was associated with greater use of goal-directed learning strategies (e.g., model-based learning) and higher Need for Cognition (NFC). These latter factors (strategic goal-directed learning and intrinsic motivation towards learning) were directly linked to academic achievement. This pattern suggests that core cognitive resources may play a supporting role in fostering the motivational and strategic processes that ultimately influence academic outcomes (though not necessarily via a formal mediation pathway in this study). External disruptions such as the COVID-19 pandemic were associated with increased substance use, particularly among students with pre-existing mental health conditions. In turn, higher levels of substance use were linked to poorer academic performance, underscoring the importance of interventions that address both mental health vulnerabilities and maladaptive coping behaviors alongside efforts to support cognitive and motivational engagement.

Appendix C

Sequential Learning Paradigm



Note. Multi-step learning and decision-making paradigm (adapted from Figure 1, Bolenz et al., 2022). Panel A illustrates the basic structure of the two-step "rocket task." On each trial, participants selected one of two spaceships, each deterministically leading to a planet (red or purple) where a drifting reward was delivered. Because two starting screens contained spaceships that led to the same planets, participants could reach a given planet through multiple paths. This structure allowed for the dissociation of model-free learning (repeating previously rewarded actions) and model-based learning (generalizing across states that lead to the same planet). Rewards on each planet followed independent Gaussian random walks. Panel B shows the stakes manipulation. In low-stakes trials, rewards were multiplied by one, and in high-stakes trials, rewards were multiplied by five. This manipulation tested whether reliance on model-based versus model-free strategies shifted as a function of potential payoff, reflecting meta-cognitive control.

Appendix D

Need for Cognition Questionnaire

Instructions: For each statement listed below, please circle the number that best reflects the extent to which you feel it is characteristic of you. For example, if the statement is not at all like you, specify 1 under 'Extremely Uncharacteristic,' or if you cannot decide, specify 3 under 'Uncertain'.

	Extremely Uncharacteristic	**Somewhat Uncharacteristic**	**Uncertain**	**Somewhat Characteristic**	**Extremely Characteristic**
1. I would prefer complex to simple problems.	1	2	3	4	5
2. I like to have the responsibility of handling a situation that requires a lot of thinking.	1	2	3	4	5
*3. Thinking is not my idea of fun.	1	2	3	4	5
*4. I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.	1	2	3	4	5
*5. I try to anticipate and avoid situations where there is likely a chance I will have to think in depth about something.	1	2	3	4	5
6. I find satisfaction in deliberating hard and for long hours.	1	2	3	4	5
*7. I only think as hard as I have to.	1	2	3	4	5
*8. I prefer to think about small, daily projects to long-term ones.	1	2	3	4	5
*9. I like tasks that require little thought once I've learned them.	1	2	3	4	5
10. The idea of relying on thought to make my way to the top appeals to me.	1	2	3	4	5
11. I really enjoy a task that involves coming up with new solutions to problems.	1	2	3	4	5
*12. Learning new ways to think doesn't excite me very much.	1	2	3	4	5
13. I prefer my life to be filled with puzzles that I must solve.	1	2	3	4	5

14. The notion of thinking abstractly is appealing to me.	1	2	3	4	5
15. I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.	1	2	3	4	5
*16. I feel relief rather than satisfaction after completing a task that required a lot of mental effort.	1	2	3	4	5
*17. It's enough for me that something gets the job done; I don't care how or why it works.	1	2	3	4	5
18. I usually end up deliberating about issues even when they do not affect me personally.	1	2	3	4	5

Note. The 18-item Need for Cognition Scale (NCS; Cacioppo & Petty, 1982; Cacioppo et al., 1984). The NCS is a self-report questionnaire designed to assess individual differences in the tendency to engage in and enjoy effortful thinking. Responses are rated on a Likert scale, with higher scores indicating a greater tendency to enjoy and engage in cognitive effort. An asterisk (*) denotes items that are reverse-scored.